Exploring first-mile on-demand transit solutions for North American suburbia: A case study of Markham, Canada

Johanna Bürstlein[a,c], David López[b], Bilal Farooq[c]

[a]*Department of Civil Engineering, Karlsruhe University of Applied Sciences, Karlsruhe, Germany*
[b]*Instituto de Ingeniería, Universidad Nacional Autónoma de México, Mexico City, Mexico*
[c]*Laboratory of Innovations in Transportation, Ryerson University, Toronto, Canada*

Abstract

On-demand transit system designs are explored for the first-mile commuting in Markham, a suburb in the Greater Toronto Area (GTA). Operational scenarios are analyzed using different types of on-demand solutions that can complement the existing GO Transit commuter train system. Various use cases of demand-responsive vehicles are explored in terms of vehicle capacity and fleet-size. It is assumed that the existing car-based trips to the four train stations in Markham would be replaced by an on-demand rideshare transit system. The on-demand transit system is simulated using the *PTV MaaS Modeller* in combination with a mesoscopic simulation, involving 1,865 trip requests within the morning peak from 7AM to 10AM. Wait-time, travel time, demand served, cost, and environmental impact are used as indicators to rate various options. Evaluating the results we came to the conclusion that three cases using vans are providing favourable outcomes. The van-based scenario using 75% of an optimal fleet size and a low detour factor turned out to be very appropriate with regard to the case study. A passenger in this scenario would at an average spend 3 minutes waiting for the service to arrive and 10 minutes in the vehicle, costing 7CAD for the ride. With a typical level of public transit subsidies applied, a 7% monthly saving is expected compared to using a private car and paying for parking fees. The scenario also results in 30% reduction in greenhouse gas emissions when compared to current personal vehicle based trips. Based on the simulation, policy suggestions for implementing the on-demand transit in Markham are presented.

Keywords: on-demand, ridesharing, first-mile transit, simulation, scenario analysis, greenhouse gas emissions

1. Introduction

Mobility is a basic necessity, the demand for which is continually changing both in terms of space and time. Due to its flexibility, people prefer to use private cars to commute instead of transit. Just in Canada, trips by car as a driver represent approximately three-quarters of all commuter trips (Statistics Canada, 2016b), despite local governments recommending to travel by transit to reduce the negative impacts (e.g. increase in congestion) of car trips. The problem of single-occupancy car trips is prevalent in the suburban and rural areas, where high-frequency public transport may not be economically viable due to the low population densities. In such areas, the utilization of transit is often low, e.g., in Canada, roughly 12% of the suburban populations exclusively use transit to commute (Statistics Canada, 2016b, D'Incà and Mentz, 2016).

Transit services can be considered sustainable mobility solutions when compared with private vehicles. Highly efficient in terms of energy and space and with more capacity, transit can be an excellent alternative to using private vehicles. The evidence of which can be observed in many high-density areas, but only in a few low-density regions. Due to spreads land use within the suburban areas, transit lines have to serve vast areas, and as a consequence, routes are longer and have low frequencies (Cervero, 1993). To keep the operational frequencies within reasonable limits, stops are spread widely and wait times can be long, which

Email addresses: `johanna.buerstlein@gmail.com` (Johanna Bürstlein), `dlopezfl@iingen.unam.mx` (David López), `bilal.farooq@ryerson.ca` (Bilal Farooq)

decreases the passengers' comfort (Batarce et al., 2015). At the same time, more vehicles are needed to serve the lines adequately, which results in high operating costs.

Due to high wait times in suburban transit, potential passengers prefer to use their private vehicles (Vijayakumar et al., 2011).The demand for transit (which is small due to the low population density) is thereby further reduced. Low demand is less cost-effective for transit operators. Hence, to ensure cost efficiency, fewer vehicles are used, which in turn decrease the frequencies or shut down the lines. This decrements on the level of service impacts the comfort of the passengers. To summarize, the low demand in suburban areas impacts the operational cost of transit, which in turn affects the quality of transport. The passengers are not satisfied with the service, so fewer people use transit. This vicious cycle is thoroughly discussed in the previous literature and is displayed in Figure 1.

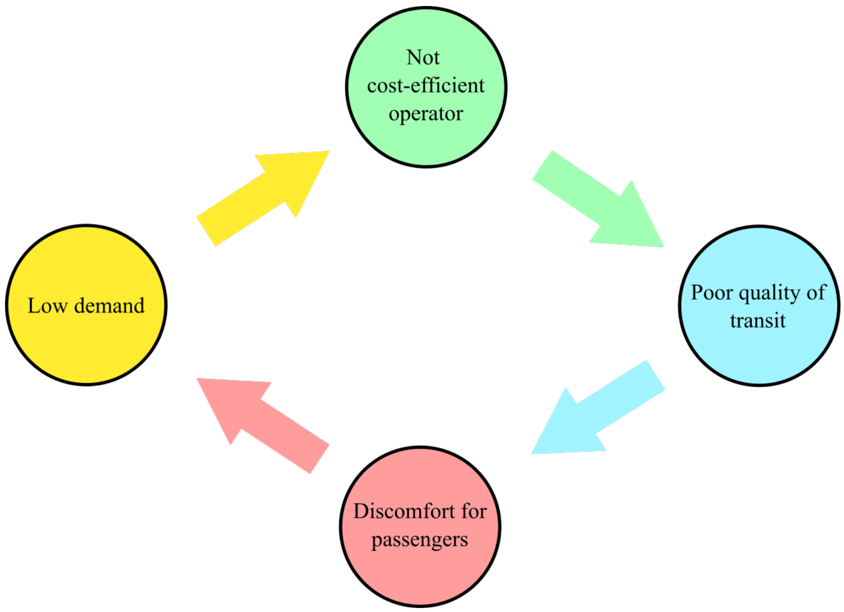

Figure 1: Dependencies in fixed route public transit operating in low-density areas

The entire journey from origin to destination can be understood as a transportation trip. Mostly multiple types of modes are used to complete the journey, e.g. walking, driving with private vehicles, cycling, taking a bus or train or a combination of modes. The core of transit trips is mostly covered by bus or rail services, but passengers need to complete the first or last portion of the trip by using other modes like walking, cycling, driving or public transport (see Figure 2).

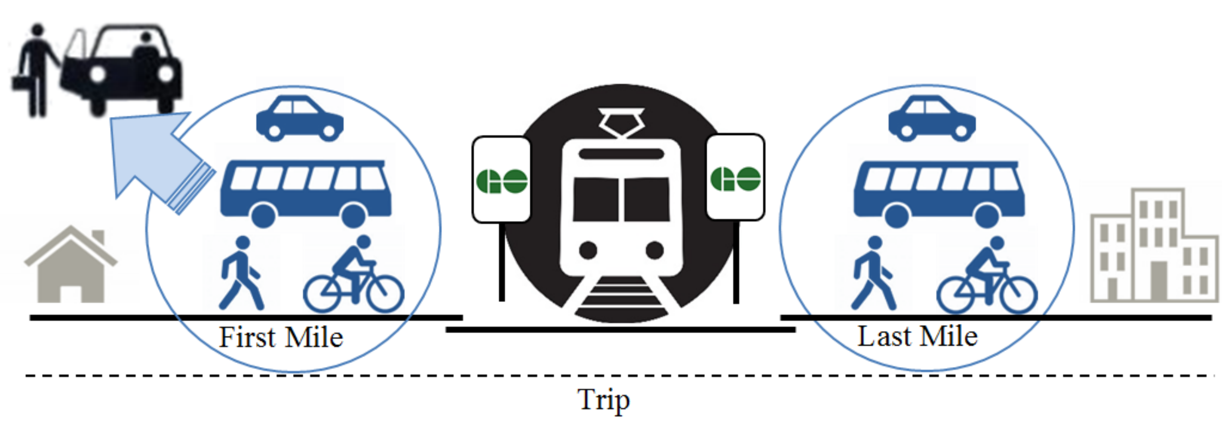

Figure 2: Structure of a commuting trip in low-density suburban areas in the Greater Toronto Area

Transportation is changing with the advent of new technologies, products and services, which can change the expectations and possibilities of people when it comes to mobility. Users, operators, companies and governments (e.g. of cities or municipalities) see the potential of mobility opportunities as a part of a big and integrated system (European Platform on Mobility Management, 2019).

Mobility as a Service (MaaS) is a system that combines various forms of transport services into a single mobility service. It was born in Finland, where it has already been incorporated into the national transport policy. Nowadays, various MaaS projects all over the world are planned or starting up (MAAS-Alliance, 2019). MaaS may improve the first-last mile connection to transit and may reduce the use of private vehicles (Wang et al., 2019). On-demand transit (ODT) systems can be part of a Mobility as a Service (MaaS) environment. Meaning the use of a transport mode combination provided from private or public transport agencies. They may run without fixed routes or timetables and include sharing and pooling rides with other passengers. These types of systems are preferred by drivers over traditional transit (Frei et al., 2017) and taxi (González et al., 2017), especially in the suburbs (Jain et al., 2017). To accommodate the first/last-mile of home-based trips, to and from transit stations, transportation agencies must find adequate and sustainable solutions. As de Jong et al. (2011) proposed, an option could be to replace first-mile driving trips with multi-occupancy ride-sharing trips and the establishment of on-demand systems.

The City of Markham, a suburb of Toronto, Canada, has all the ingredients to implement an ODT system for first-mile trips. In Markham, local transit is barely used within the first-mile commuting context, but at the same time, the regional commuter train to downtown Toronto is in high demand. This study explored the effects of implementing a demand-responsive transit system in the City of Markham. Operating an on-demand service for the first-mile in this area could change the commuter's experience positively. Problems like congestion (Teodorović and Orco, 2008), long travel times and travel costs (Furuhata et al., 2013) can be tackled because single occupancy trips could be converted to multiple occupancy trips.

A simulation and an evaluation of an on-demand transit (ODT) for first-mile trips in the city of Markham is presented. The authors use the definition of Ronald et al. (2017) to describe an ODT with the following characteristics:

1. Schedules are fully flexible.
2. Routes are fully flexible and only serve within the Markham limits.
3. Two fleet sizes are considered (cars and small vans).
4. Pick-up points are designated and located near the households of the passengers.
5. Drop-off points are four regional train stations in Markham.
6. Passengers can only be picked-up and dropped-off at the designated areas (points 4 and 5).

The rest of the paper is organized as follows. In Section 2, examples of ODT systems in Ontario, Canada are presented and it is discussed the latest research on ODT simulation in low-density areas. An overview of the research area and the corresponding demand in Markham are presented in Section 3. Accordingly, the methodology which is used to create the scenario cases is described in Section 4. Results are presented in Section 5. Future work and conclusions regarding policy implementations for a successful ODT implementation in Markham are presented in Section 6.

2. State of the art

On-demand transit systems have been successfully implemented in some suburbs around the globe. In Milton, Toronto, the public transit agency, together with a company called *RideCo*, improved access to the local train stations and reduced reliance on an overcrowded parking lot by implementing an on-demand ride-sharing service. After one year, the pilot authorities found that the net cost per ride was 27% less when compared to the price of the municipal bus (RideCo, 2018). In the town of Bellville, Ontario, authorities implemented an on-demand late-night bus for reducing operating costs and enhancing convenience (Sanaullah et al., 2021). The authorities of Innisfil, Ontario, started subsidizing *Uber* and taxis rides, hypothesizing that this strategy was more cost-efficient for the town than running the bus lines (Pentikainen, 2016). Kamau et al.

(2016) implemented and evaluated an on-demand transit pilot in Dhaka, Bangladesh, observing reductions on wait time up to 44%. Cities like Munich (MVG, 2018) and Mexico City (Jetty, 2019) are implementing on-demand van services where routes are computed considering the passenger's destinations and seat availability.

Modelling on-demand transit has been an active field for several years since it is a transportation mode that could mitigate congestion and may help to improve the service level of transit agencies. In 2004 Cayford and Yim proposed a mixed transit system that operated as a normal transit during peak hours, while in low-demand periods, vehicles deviated from routes and alter schedules to serve on-demand passengers and thus improving the level of service during this period. On the operational side, Djavadian and Chow (2017) proposed a methodology to evaluate different policies and scenarios such as fleet sizing and fare prices to create financially viable on-demand transit systems. Also, Wallar et al. (2019) proposed an algorithm that optimized fleets and routes to serve all the demand in selected periods. Daganzo and Ouyang (2019) created a general model to simulate all types of demand-responsive transportation, including ODTs. The study claimed that while the model developed was not perfect, but it might be used to systematically explore operational and pricing strategies.

Although some ODTs have been successfully implemented, this mode is not widely available, but some researchers (de Jong et al., 2011, Frei et al., 2017, Archetti et al., 2017) suggested that ODTs may find a niche in first/last-mile trips; some of the latest works on this subject are reviewed as follows. Liang et al. (2016) optimized two schemes for a first/last mile on-demand automated taxi service. The first scheme maximized the profits of the taxi operators by being free to accept or reject the trips, leading to a poor level of service. The second scheme guaranteed that the demand in selected service areas was satisfied. The authors use linear programming for modelling and optimizing the schemes. They presented a small case study in Delft, Netherlands, testing different fleet sizes on the two schemes and discussed the implications of satisfying the demand or increasing the profit. The authors also tested the impacts of having a fleet of electric versus conventional vehicles and automated versus human drivers. Bian and Liu (2017) proposed a tool for ODT that matches passengers with routes. The developed tool only considered one train station as the destination and the passengers could specify the train they would like to board. The tool was intended for first-mile trips and only minimized the travel time constrained by the passengers' train boarding schedule. Franco et al. (2020) used aggregated mobile phone network datasets and the transport simulator, *MatSim*, to develop an agent-based model. The authors proposed an on-demand transit for first-mile trips in the North of Bristol where the transit has poor coverage. Their simulation showed that an ODT could replace the transit in certain areas, however when a pilot study was implemented the service could not reach the expected patronage because of the small scale of the pilot. ODT and autonomous vehicles (AV) may create a good synergy and reduce operational costs in the first/last-mile trips; Shen et al. (2018) simulated an ODT for Singapore where AVs replace some low-demand routes that serve first-mile trips. The study found that if 10% of the low-demand routes are replaced by AV the overall waiting time and travelled kilometres is reduced. However, if more share of AV were used the system performance worsened. Sieber et al. (2020) simulated an ODT with AVs to connect rural areas to cities in Switzerland. Their simulation consisted in replacing low-demand rail routes with an ODT and concluded that the ODT would bring benefits in terms of operational cost and level of service. In the AV-ODT model of Chen et al. (2019) the passengers made trip requests ahead of time and the system dispatched vehicles in time horizons, i.e., when passengers requested a trip, their vehicle would be dispatched in the next time horizon when the request was made. The study used two mixed integer linear programming to compute the minimum operation cost and user total travel time, and then compared the performance of the system in both cases. Salazar et al. (2020) simulated an AV-ODT and its interactions with the transit systems of New York and Berlin. The study found that the integration of the AV-ODT and current transit system brought greater benefits (cost, reduced emissions, congestion) compared to an AV-ODT system operating in isolation.

This study presents a simulation and evaluation of an ODT for first-mile trips in the city of Markham, considering realistic travel times and waiting times. It is evaluated how changing parameters like fleet size, detour factor and vehicle capacity affect the total travel time. The current transit system is not considered in the simulation as it is assumed to be replaced by the ODT service. The main contributions of the paper are highlighted as follows: (1) a systematic spatial analysis of the study area to develop a case for ODT in Markham, (2) comprehensive ODT system design analysis with different combinations of vehicle types, fleet sizes, detour factors, and detour times to find an 'ideal' fleet that can serve most of the users with least waiting and in-vehicle travel times, (3) a cost comparison analysis in terms of fleet size and detour factors,

(4) a cost analysis comparing the ODT cost to the use of private vehicles for first-mile trips, and (5) based on the simulation analysis, detailed policy suggestions for implementation of the ODT service in Markham.

3. Case study and descriptive analysis

Markham, Toronto, is part of the Greater Toronto Area (GTA) and is located in Ontario, Canada. It has over $355,000$ residents. It is home to more than $1,500$ high-tech and life science companies and around 210 multinational firms (Markham.ca, 2018). In the past few years, Markham has gone through a phase of strong development. By 2023 Markham is expected to grow by 8.4% its population, which is considerably high when compared with the national growth of 4.8% or the City of Toronto's growth of about 4.1% (Statistics Canada, 2016a). With a higher population, the demand for transportation is also going to increase, which is leading to the conclusion that traffic jams would also grow if the traffic infrastructure is not changing. Congestion is already a major issue faced in downtown Toronto, where many residents of Markham commute to and from for work. Due to this, many choose the regional commuter train service, GO Transit, to reach the downtown area of the GTA.

GO Transit is a public transport operator of the GTA and provides service to downtown Toronto. Within the municipality of Markham there are four train stations as shown in Figure 3. *Unionville* station is closest to *Union Station* (downtown main GO station), and a trip by GO Transit takes about 41 to 46 minutes during the morning peak. Passengers from *Centennial* GO station to *Union Station* have to plan their trip with an in-vehicle time of 53 minutes. From *Markham* GO station to *Union Station*, a train takes 58 minutes and from *Mount Joy* GO station 63 minutes till it reaches its destination at *Union* GO station. During the morning peak from 7 to 9 am, the in-vehicle times are slightly higher than during the day. Within the day, the connections are changing and direct trains are not always available. In this case, passengers have to reach *Unionville* station and take the GO bus from there (Gotransit, 2019). Langstaff GO Transit station (bottom-left part of Figure 3) is located outside the Markham municipality, therefore it is not considered in the study.

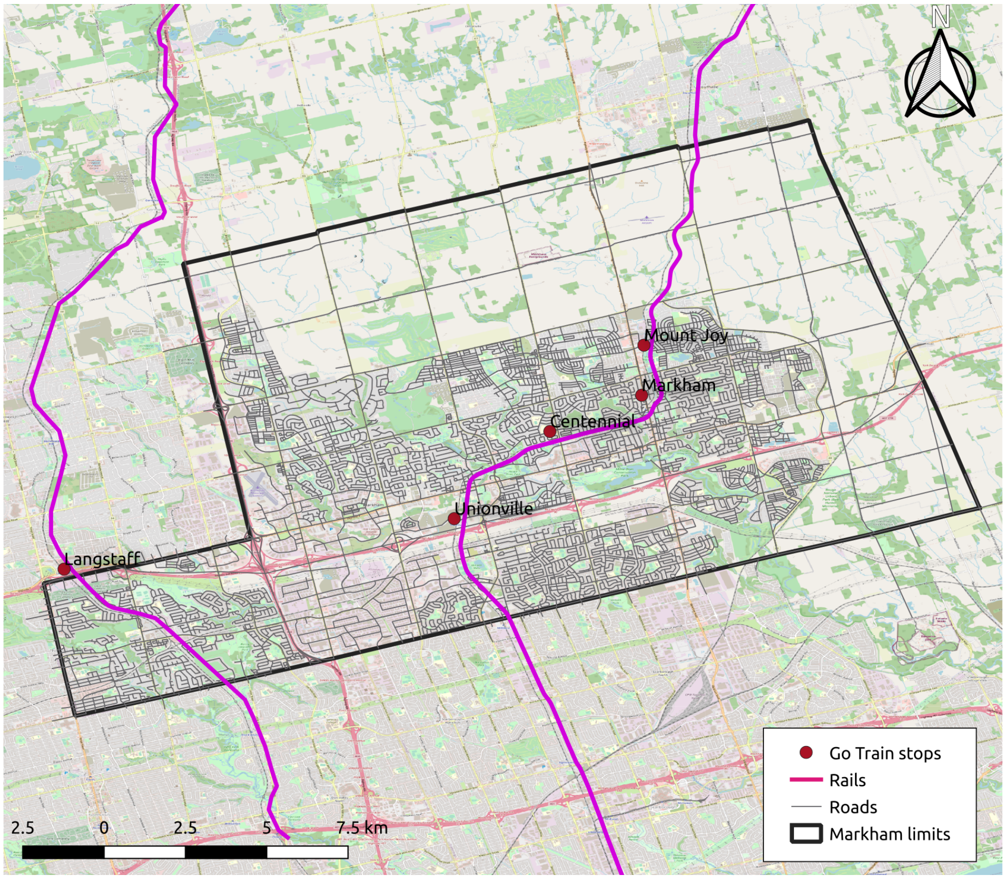

Figure 3: GO Transit stations located in Markham

Markham inhabitants highly depends on cars, more than two-thirds of all the trips in Markham are done by car, while the second most common transport mode is travelling as a passenger. Together they represent almost 90% of all Markham trips. In fact, most of the households in Markham own at least one car and most of them can afford two cars (TTS, 2016).

3.1. GO Transit and its demand

Markhamites use the GO Transit to commute to downtown Toronto daily. The Transportation Tomorrow Survey (TTS) (TTS, 2016) provides data about which stations of the study area are frequented and which modes are used to get to the stations. Figure 4 presents the modal split of $1,865$ first-mile trips to *Unionville*, *Markham*, *Centennial* and *Mount Joy* GO Rail Station defined by time periods. Times displayed on the x-axis are rounded to 15-minute intervals and represent the starting times of each trip. The blue and grey colours are dominating all the diagrams. Hence a high percentage of trips are made by car. Blue represents trips of people driving cars and grey signalizes that the trip is made as a car passenger. As blue overcomes the grey, this leads to the insight the most trips are single occupancy trips. It is visible that *Unionville* station is highly frequented, especially during the morning peak from 7am to 8am. Due to the travel time to downtown, it is likely that most trips start around this time because most people start working between 8am and 9am.

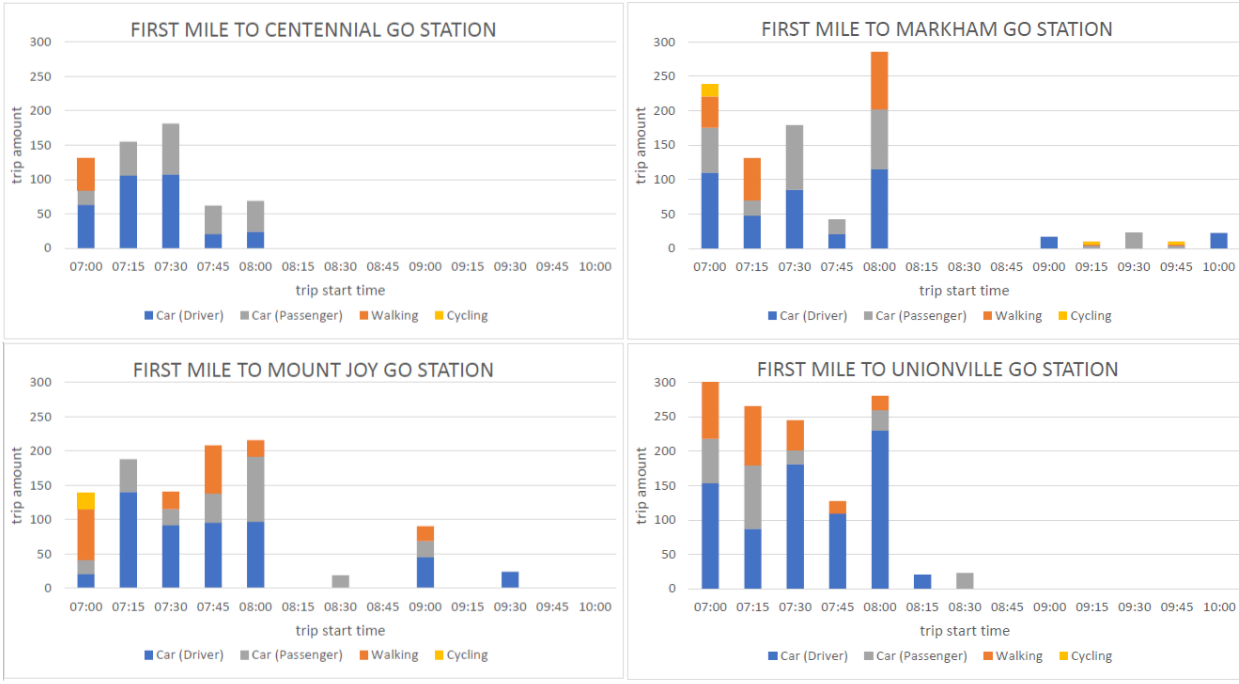

Figure 4: Modal split of the first-mile trips to *Unionville*, *Markham*, *Centennial* and *Mount Joy* GO rail stations

The green bars in Figure 5 (TTS, 2016) show the number of car trips per Traffic Analysis Zone (TAZ), going to the GO Transit stations from 7:00AM to 10:00AM—thus representing 5,544 first-mile trips by car to the GO Transit stations. Only the trips originating in Markham are taken into account, as we are assuming the operating area of the proposed on-demand transit to be within Markham's borders. As shown in Figure 5, most of the trip origins are close to the nearest GO station. However, due to the extensive geographic area of Markham, commuters travel longer distances to get to the train stations. The TAZs in Markham (the colored areas in red tones) have an average area of 1.9km^2 and an average population density of 2,300 person per km^2. *Unionville* is the highest used station, because it is the closest station to Markham downtown and its closeness to a highway makes it easier to access. Figure 5 shows the population density of the TAZs, note that most of the car tips are originated in areas with high population densities. The south-western Markham does not have any first-mile trips to Unionville, Centenial, Markham or Mont Joy, since this area is served by the Langstaff station. These trips are not part of our current study.

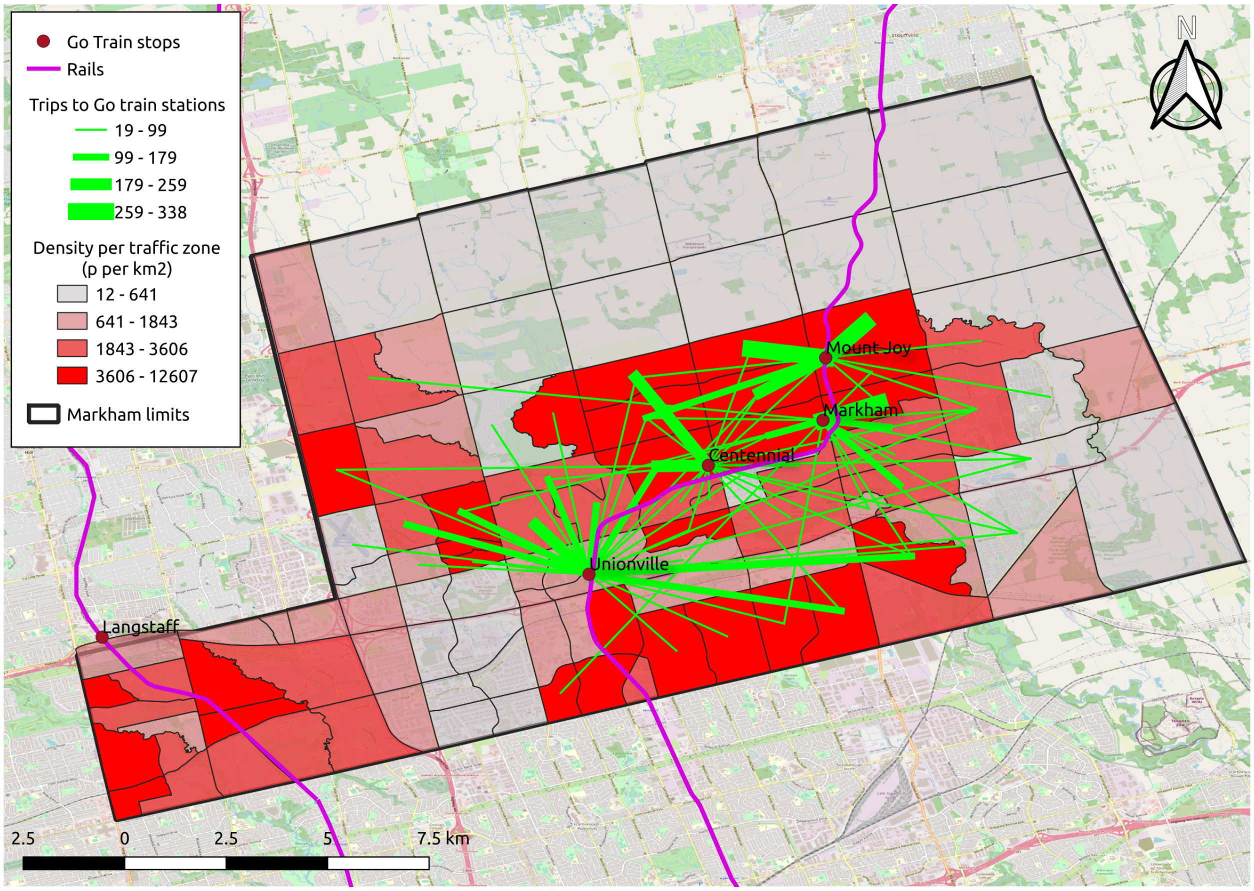

Figure 5: Population density in traffic zones and car trips demand from 7:00AM to 10:00AM to GO Rail stations

Figure 6 shows the population density per TAZ and the current Markham transit network. The fixed route transit network is fairly dense, however as previously pointed out, the data show that 90% of the population prefers private vehicles for commuting. There could be several reasons that explain the low share of fixed route transit e.g. long waiting times, comfort, and higher-income. Other points that might contribute to the high share of private vehicles is the long distances and the suburban sprawl of Markham. As shown in Figure 6, very few people live within a walking distance of the train stations, (see the 400m green buffers around the stations). The road network of the municipality is comprised of large blocks, cul-de-sacs, and curved streets, which makes it hard for the pedestrians to walk shorter distances or to easily access a bus stop. In this context, it is fair to conclude that the proposed on-demand service will have a higher acceptance rate as the ubiquitousness of the pickup/dropoff locations will reduce the walking distances, while on-demand booking service will mitigate the waiting times and parking cost.

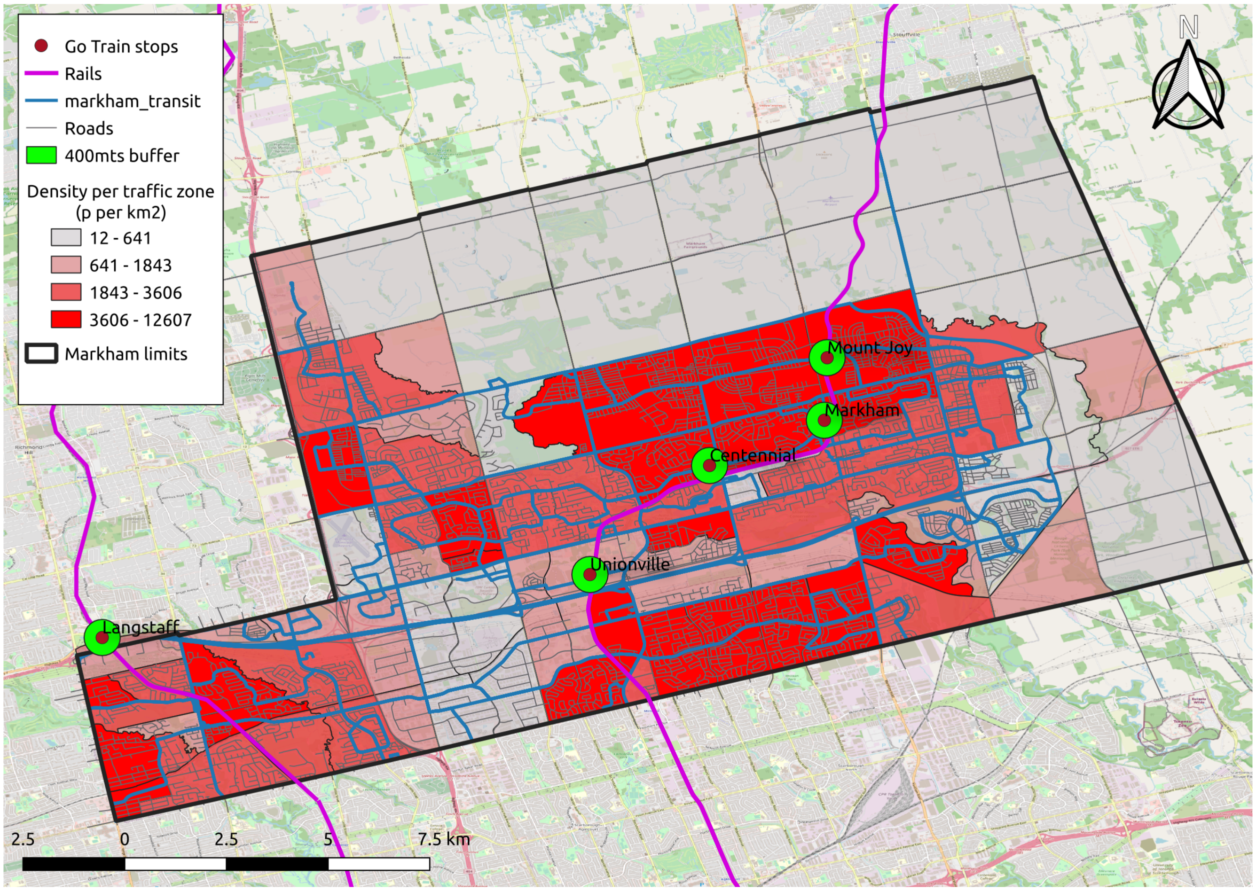

Figure 6: Population density in traffic zones and transit network

4. Methodology

The ODT service for the first-mile access to the Go stations in Markham from 7:00AM to 10:00AM is simulated using the *PTV MaaS Modeller*, which is one of the few specialized simulation tools currently available. Each scenario is simulated with 5 replications to generate the results, which take 60mins at an average to run on an Intel i7 desktop. To simulate the scenarios, we first needed the link travel times and demand at the pick-up and drop-off points. For the link level travel times a macroscopic simulation was developed using *PTV Visum*. We chose to use a macroscopic simulation because the detailed impact of single intersections and vehicles are not of importance for the level of service evaluation of the ODT system. In addition a macroscopic model provides outcomes to a satisfying degree with regard to the developed indicators. We chose to use *Visum* because we needed to simulate a range of scenarios and the software offers a fast execution speed. The simulation was calibrated using the cordon counts as well as Google travel time data. By using the dynamic stochastic traffic assignment, the volume and impedance of each link are calculated. Using the free-flow speed and link capacity, the free flow travel time, speed and time for each link and path were computed. The Pick-Up and Drop-Off points (PUDOs) were selected at the nearest local intersections and ensuring that the average walking distance to the location remains 200m. The demand at these PUDOs was then calculated using the TTS trip data. Next, we present the computation of the link travel times, PUDOs location and the ODT simulation setup.

4.1. Link travel times

The demand data used to represent the status quo consist of expanded trip demand of the Transportation Tomorrow Survey of 2011. The trip demand is then projected to the year 2018 with a growth factor that corresponds to the population growth of Markham. Based on this data, a traffic assumption is made, which shows the expected demand in the number of trips made within Markham and trips originating or ending in Markham. Trips relating to the GTA with one end in Markham are assigned to cordon zones around Markham's border. Traffic volumes for the base case are shown in Figure 7, representing the dynamic stochastic assignment between 7AM and 10AM. Most traffic is on the highway (displayed in red in Figure 7), which crosses Markham in an east-west direction.

Figure 7: Traffic volumes of the Base Case between 7am and 10am

Traffic counts of the program Cordon Count Data Retrieval System (TTS, 2016) are used to calibrate the system. Figure 8 shows which screenlines are within the borders of Markham. As it is only one suburb of a larger region, there is only one screenline available for the research area. The total traffic volume from 6am to 10am sums up to $70,000$ vehicles. After the first simulation of the base case, the software calculated roughly $35,000$ vehicles on the streets of screenline 11. As the traffic volume is not matching the screen line, it is expanded with a factor of two.

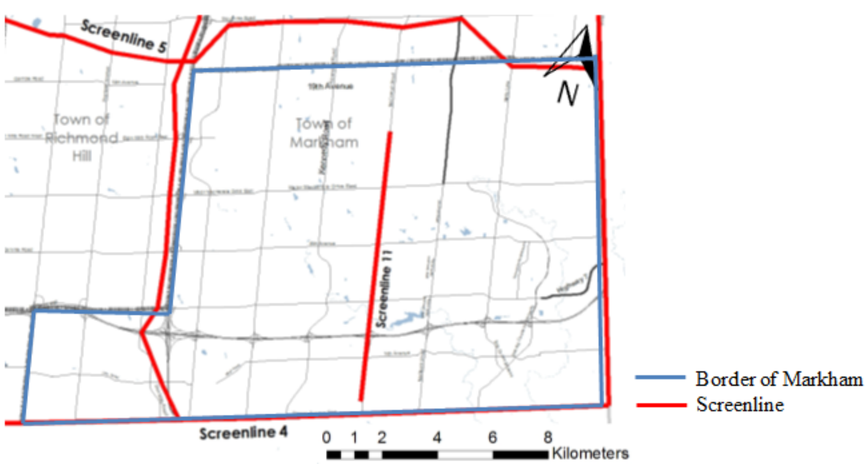

Figure 8: Location of screenlines within Markham

Additionally, we ran a new base case simulation with the adjusted traffic volume (i.e., considering the expanded and projected trip demand for 2018) and compared it with the travel times obtained from Google API, considering the average congestion of a random Thursday at 8am in Fall 2018. Figure 9 shows the boxplots of travel times from all TAZ centroids to the GO Transit stations. The blue boxplots show the results of the simulation with the adjusted traffic volume, while the red ones show the results of *Google* travel times. As seen on Figure 9 both boxplots have a similar interquartile range and median, so the dispersion of both travel times is fairly the same. The minimums of both boxplots are approximately the same, while a larger difference on the boxplots is observed for the maximums. It is possible that we are overestimating the travel time for longer trips, but the overestimation is only by 5 minutes. Both batches are on the top-skew, although the top-skew is less evident for the Google travel times. Since both datasets have similar characteristics and occur on similar time frames it is concluded that the travel times of the simulation and the travel time of the Google API are close enough, so no further calibration on the system was made.

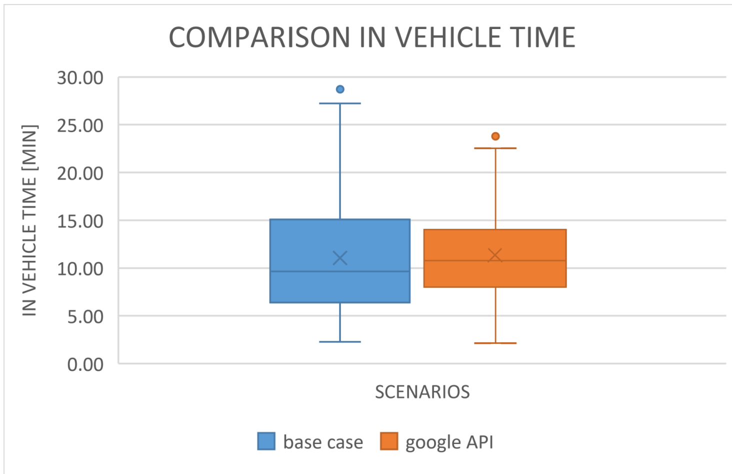

Figure 9: In-vehicle travel time of the simulation vs. travel times obtained with the google API. The box height represents interquartile (from Q1 to Q3) dispersion of the data. The 'x' marks the mean of the travel time. The horizontal line represents the median of the travel times. The vertical line (whiskers) is the variability of the travel times outside Q1 and Q3. The dots outside the whiskers are the data outliers

4.2. PUDO locations

In the proposed ODT, the pick-up points are fixed, like regular transit, but for improving the service level, the locations of pick-up points must be dense and close to the user location. Since the ODT is intended for first-mile trips ending at the GO Transit stations, the location of pick-up/drop-off points (PUDO) are assigned to intersections, such that these points are on average at 200m from every household in the block. The density and proximity of PUDOs from every household avoid users to walk unrealistic distances. A detailed map of all PUDOs is shown in Figure 10. The density of PUDOs in the north and east part of Markham is scarce, because most of these areas are farmlands and the households are only living near the major intersections.

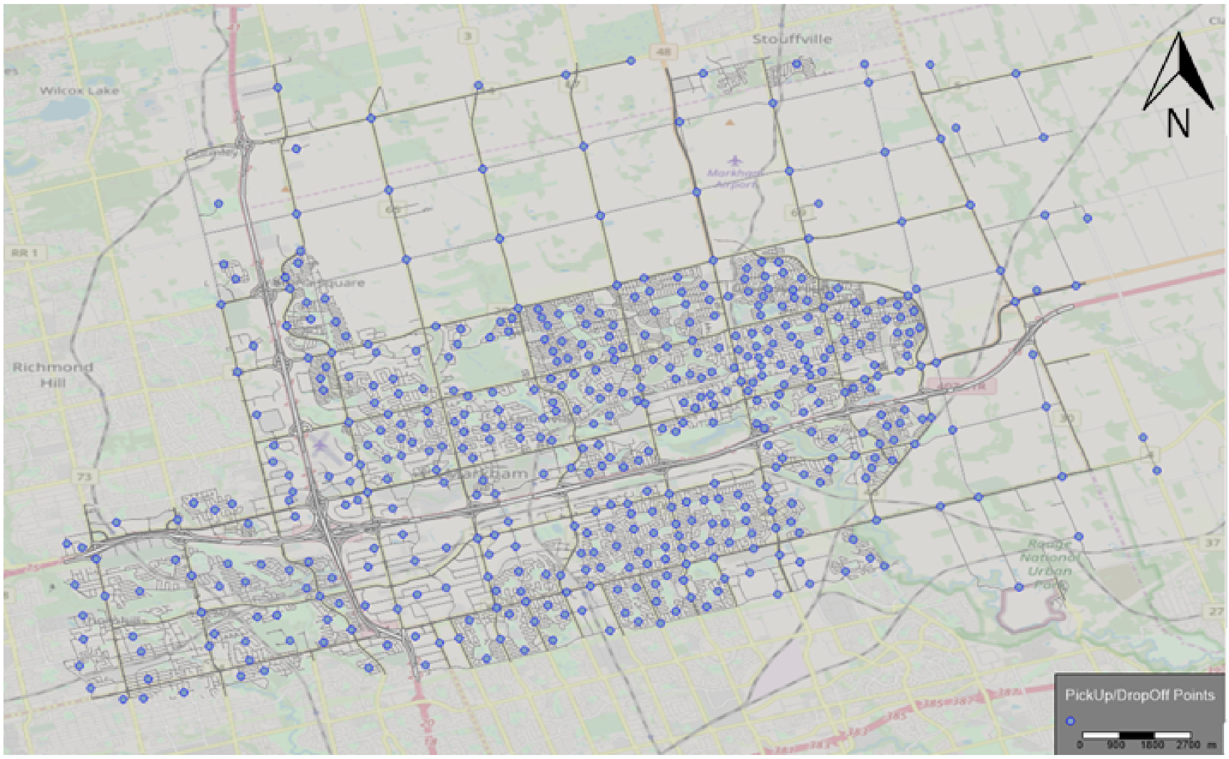

Figure 10: Pick-up/Drop-off Point (PUDO) locations

4.3. ODT simulation

In contrast to conventional public transport, ODT systems can follow fully flexible schedules and routes. In this study we model trips starting from many origins and ending at exactly 4 destinations (GO Transit stations) operated by 4 or 7 seater vehicles. The service does not offer a door-to-door pick-up/drop-off but is delivering the passengers to fixed stops (see the PUDOs in Figure 10). For modelling such a system, the *MaaS Modeller* tool of *PTV Visum* provides the option to model on-demand services as a rideshare solution. Thus the simulation case can be part of a future MaaS environment in Markham connecting regional with local public transit. Basically the modeller follows two steps; (1) trip request generation and (2) tour planning.

In a nutshell, the *MaaS Modeller* works as follows. The operator provides a vehicle fleet to meet the demand and defines; (1) waiting-time bounds and (2) travel time bounds, known as detour factors, to increase utilization of the vehicles and to accommodate several passengers on a given vehicle. In an on-demand rideshare system, not all trip requests are known prior to the tour planning. Since it is not possible for the *MaaS Modeller* to dynamically simulate trip request, the tour planning simulation is divided in time-slices of 15 minutes for modelling the dynamics of incoming trip requests from the PUDOs, i.e., all the expected trip request for the 15 minute time-slice are made at the beginning of the time-slice and a tour is planned for these requests. For the next time-slice, a new expected trip requests are computed and the request not served on the previous time-slice are discarded (later in the text we will discuss about this). The choice of 15 minutes time-slice for the simulation fits very well with the schedule of GO Transit in the morning peak hour. The trains arrive at GO Transit stations every 15min, so selecting the shorter or longer time-slices could cause users to wait longer at the stations or may result in the users to miss their train.

4.3.1. Trip request generation

In this study, it is assumed that all the first-mile car trips are replaced by the ODT system. Hence, the trip requests at each PUDO every 15 minutes is obtained by randomly distributing the zonal level car-trips (see Figure 5) to the PUDOs contained in a TAZ. This procedure allows to simulate users request to the ODT that include desired the pick-up time, origin, and destination. PUDOs are used to enter and exit the ODT system. It is assumed that the paths resulting between start/end (household/GO Transit station) nodes and pick-up/drop-off nodes must be covered on foot, which is not more than 200m. As the walking distance is very short, it not considered in the evaluation of the ODT system.

When a trip request is placed, the closest PUDO to the user location is assigned. Given the 15 minute time-slice for modelling the trip request dynamics in *Mass Modeller*, the ODT simulation restricts the wait time at a PUDO to a maximum of 15 minutes, past this time the request is discarded and is not considered in the next time slice. Each ride is shared with other passengers and it is assumed that the total travel time and the number of passengers sharing the ride does not influence the mode choice behaviour. We believe that this is a valid assumption, as the passengers are already sharing the rest of the ride in GO Transit.

4.3.2. Tour planning

The tour planning process matches the demand (the generated trip requests at the pick-up points) with the supply (the vehicle fleet). Skim matrices derived from the traffic assignment (see Section 4.1) are used to extract the travel times between all PUDOs. By solving a variation of the Travelling Salesperson Problem (TSP)[1], the tours are computed to serve as many trip requests as possible, considering: (1) fleet size, (2) seat capacity of fleet vehicles, (3) maximum waiting time, (4) detour factor and (5) maximum detour time. The detour factor is the ratio between the additional travel time and the minimum travel time of the tour (Wang et al., 2020), e.g., a detour factor of 1.5 indicates that the total travel time of the tour should not be longer than 1.5 times the minimum travel time. The maximum detour time is defined as the difference between minimum travel time and total travel time, e.g., a maximum detour time of 30mins means that any given tour cannot be longer than the minimum travel time plus 30mins.

The *MaaS Modeller* tour planner selects requests depending on the effect they cause for the whole tour. Negative effects like long waiting times or large detours, might lead to a vehicle to drop a request[2]. However, this request can be included in a different tour of another vehicle within the maximum wait time. The requests which are still open and are not causing high negative effects are pooled[3] for service in a way that passengers travel under almost equal conditions. According to that, the experienced detour factor and travel time are minimized. As soon as the maximum wait time has elapsed, the request is considered as unserved. To schedule the vehicle utilization, *MaaS Modeller* tour planning only uses the trip requests known in the current time-slice, unserved requests from previous time-slices are discarded. The vehicle positions are adopted from the current or the previous time slice, i.e., no rebalancing of fleet is incorporated. The optimization aims include: (1) meeting as many trip requests as possible within the defined temporal (time-slice) and spatial restrictions (PUDOs) and (2) using the least possible number of vehicles.

The diagram shown in Figure 11 summarizes the steps of the on-demand transit simulation. The blue part in Figure 11 shows how the travel time of the links are generated. The purple part shows how the demand of trip requests is generated. Finally, the green part shows how the tours are planed.

[1]Since the *MaaS Modeller* is a proprietary software the exact heuristics for solving the TSP variation are unknown. Given that the computation times are short (5min per time-slice), we can be sure that the solution is sub-optimal.

[2]The heuristics/algorithms for selecting the request with negative effect were not disclosed.

[3]The exact pooling mechanisms are also not disclosed.

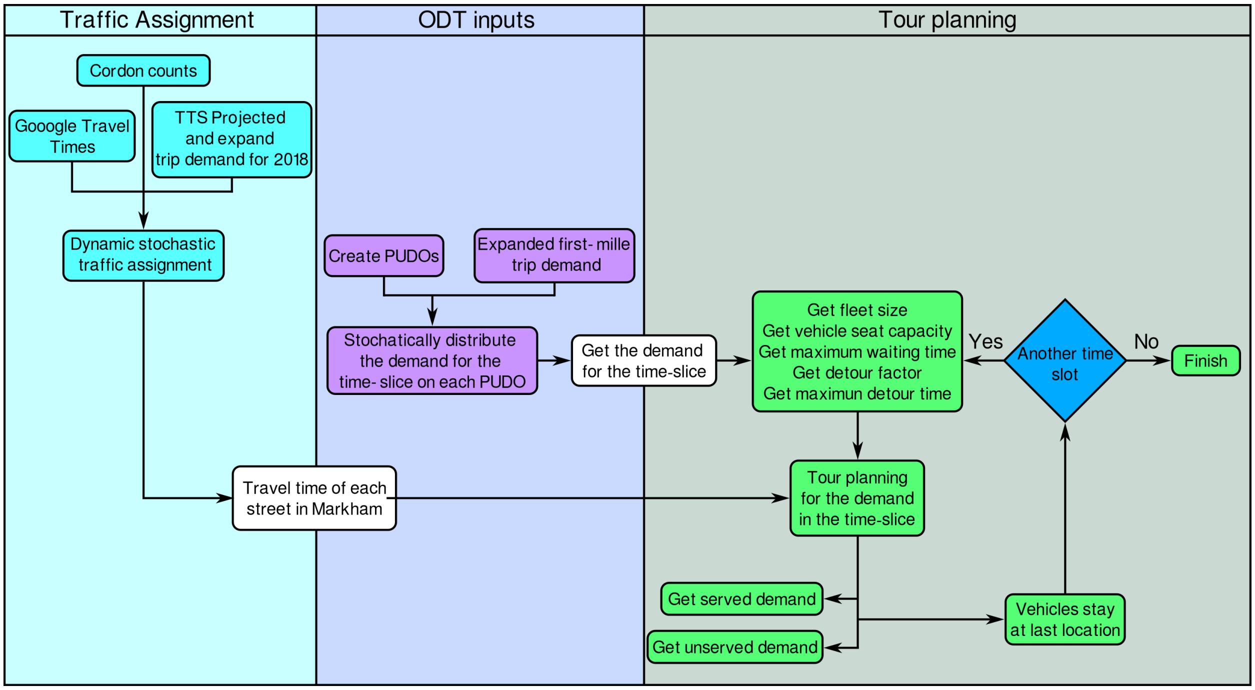

Figure 11: Conceptual diagram for the ODT system simulation

4.4. Design scenarios simulated

Four simulation groups are developed and compared to evaluate the ODT system design in terms of: (1) the in-vehicle travel time, (2) wait times, (3) vehicle occupancy, (4) served requests, and (5) unserved trip requests. The simulation groups are shown in Table 1 and consist of different combinations of vehicles types, fleet sizes, detour factors, maximum detour times and passengers expected on each trip request. The fleet in each simulation is homogeneous and two vehicle types are tested, one fleet is composed by vans (7 passengers), while the other is composed by cars (4 passengers). In the *MaaS Modeller* version used for this simulation, it is not possible to set an heterogeneous fleet so no results are provided in this regard. In each simulation group different fleet sizes are tested, such that: (1) 100% of the *optimal supply* is served, (2) 75% of the *optimal supply* is served, and (3) 50% of the *optimal supply* is served. Such that, the *optimal supply* is the minimum fleet size needed for serving all trip requests. To compute the *optimal supply* an "infinite" fleet size with detour factor of 1.5 and maximum detour time of 30mins is simulated. With this setup, the *optimal supply* for an ODT system in Markham with cars is 215 vehicles, while the *optimal supply* for vans is 165 vehicles.

According to the 2011 TTS around 52% of the first-mile trips going to a Go Transit station are made by a driver, while the other 48% are made by a passenger. To protect the privacy of individuals, from the TTS data it is not possible to match drivers and passengers and know how many passengers and drivers are going to the GO Transit in the same car or to know how many passengers are going to the train station, but the driver would continue the trip somewhere else. Downtown Toronto has the highest number of jobs in the GTA with around 40% of the workplaces located in the City of Toronto (Toronto City Planning, 2016), so it is likely that both driver and passenger are going together to the GO Transit stations. Furthermore, there are not enough data available to estimate how many passengers are going to the train station and then the drivers continue the trip somewhere else. In this study, we assumed that 50% of the first-mile trips going to the GO Transit stations are made by one person (just the driver or a person being driven to the station), while the other 50% are made by two people (both persons in the car going to the train station). Hence for each simulation case, it is assumed that 50% of requests are for one person, while the other 50% are for two.

Table 1: Simulation cases

Simulation group	Vehicle type	*Optimal supply*	% of *optimal supply*	Detour factor	Maximum detour time	Passengers per trip request
1	Van (7 seats)	165	100%	1.5	30	50% of the request expect 1 passenger and 50% of the request expect 2 passengers
			75%			
			50%			
2	Car (4 seats)	215	100%			
			75%			
			50%			
3	Van (7 seats)	165	100%	5	60	
			75%			
			50%			
4	Car (4 seats)	215	100%			
			75%			
			50%			

5. Results

The results for a detour factor of 1.5 are displayed in Figure 12 and show that the unserved demand increases with the decrease in available vehicles. This effect is stronger for van-based cases because the seating capacity in the van is higher. One van can pick up a maximum of seven different trip requests, whereas one car can pick up a maximum of four trip requests. If fewer vans are available, more trip requests are ending up not being served than if fewer cars are vacant. So the number of unserved trips rises faster. For the *optimal supply* case, all trips are served, whereas for the scenario with 75% of *optimal supply* and both vehicle types, 5% of all requests are not served. The results for the scenario with 50% of *optimal supply* state that cars are performing better and can serve about 10% more requests than vans.

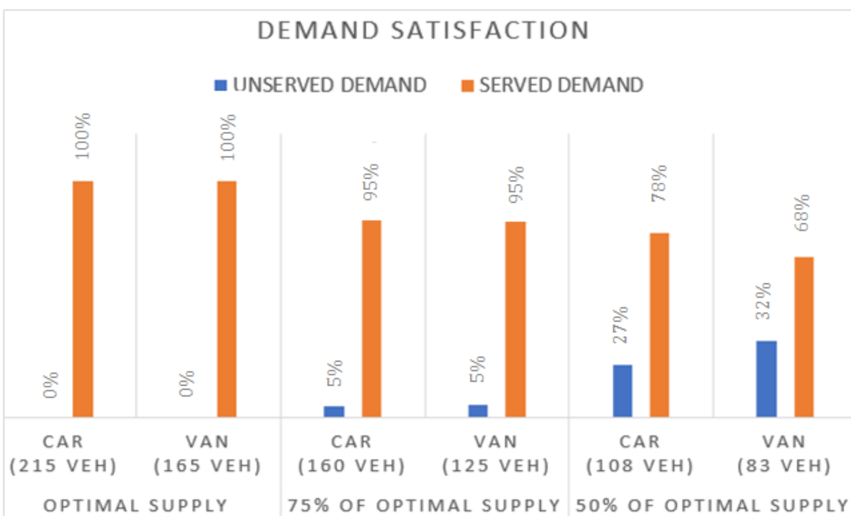

Figure 12: Demand Satisfaction ODT (detour factor 1.5)

If the vehicles (vans or cars) were to serve each and every trip, the detour and travel time would increase tremendously. It does not happen in the simulation because the detour factor is limited. To demonstrate the impact of a higher detour factor, another simulation run is operated and the results are shown later in the section. If the detour factor is not limited, travel times would increase and passengers may experience a poor quality of service that may lead to less utilization of the service. Unfortunately, the *Maas Modeller* does not allow running simulations without detour factor, so the impacts can not be stated with certainty.

The occupancy rate of the operating vehicles for each supply state is shown in Figure 13. The unserved trips are included in bars with zero seat occupancy. Comparing car-based and van-based scenarios, the share of occupancy develops in the same pattern for all supply states; 75% *optimal supply* scenario counts almost always the most trips per seat occupancy followed from *optimal supply* and 50% of *optimal supply* cases. Just for vehicles with zero or full occupancy, this order changes when the 100% of *optimal supply* and 75% of *optimal supply* are changing. What is remarkable is the fact that the number of vehicles with full occupancy decreases when lesser vehicles are available. The expected behaviour would have been a higher occupancy when fewer vehicles are available to serve more requests. This examined phenomenon is explainable with the limitation of the detour factor to 1.5, which is influencing the maximum allowed detour. For example, a vehicle with two passengers receives a request to pick up a third passenger, but the additional pick up causes detour and a tremendous increase in total travel time. Accordingly, the passenger is not picked up.

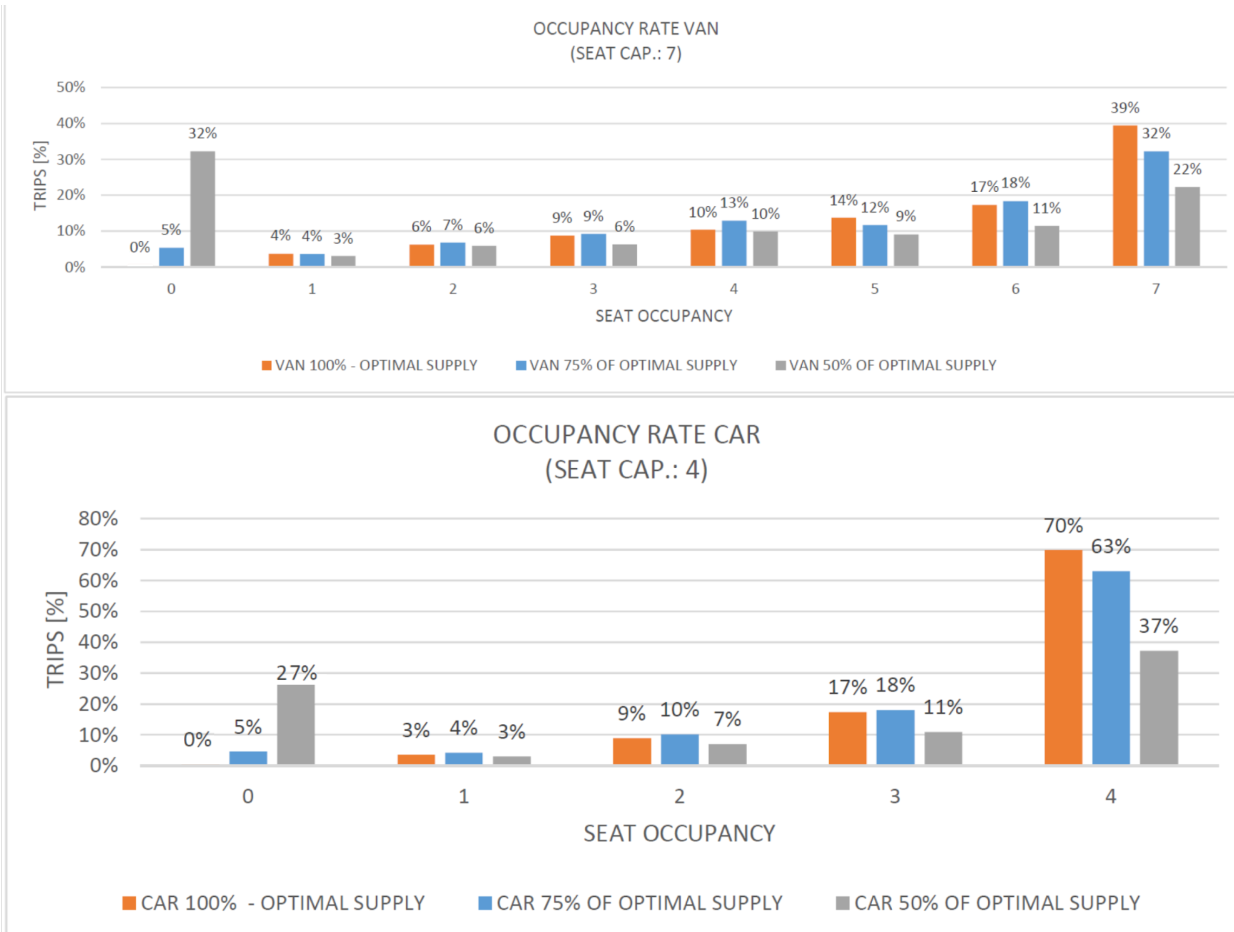

Figure 13: Occupancy Rate of ODT (detour factor 1.5)

When reducing the number of vehicles, also the frequency is reduced. That means that for a certain time period, less vehicles are available, and as such, not all requests can be assigned. Additionally, when focusing on the 50% of *optimal supply* cases, the already small number of vehicles is assigned quickly and no available vehicles are remaining for the current time slice. Because of this, the number of unserved trips is much higher for the case with 50% of the *optimal supply*. Another possible outcome of a reduced fleet size can be a higher occupancy of the vehicles, but this depends on the realization of trip requests. As mentioned in Section 4.3.2, the tour procedure tries to plan all known requests in the most efficient way and builds tours for the vehicles. Trip requests that would cause high detour for the vehicles and passengers are not regarded. The requests that are still open and are not causing large negative effects are pooled in a way that passengers travel under almost equal conditions. According to that, the experienced detour factor and travel time are minimized. This explains the high rise of unserved demand and fall of fully occupied vehicles when reducing from 75% to 50% of the *optimal supply*.

In-vehicle time and wait time at the PUDO per supply state from 7am to 10am are discussed next. The outputs for in-vehicle time are presented in boxplots and shown in Figure 14. The main in-vehicle time for car-based trips and *optimal supply* is reached from 7:12 to 11:15 minutes, with a median of 8:43 minutes. For trip requests served by car, a mean in-vehicle time of 09:18 minutes is calculated for the car-based *optimal supply*, which is about one minute smaller compared to the van-based *optimal supply*. This could result because of a higher seat capacity of the vans and is also the reason for the discrepancy between car and van-based 75% and 50% of *optimal supply* cases (vans are making more stops, so they lose time). The more trips requests are served per vehicle trip, the longer is the distance covered and the in-vehicle time increases. In-vehicle time decreases slightly for 75% and 50% of *optimal supply*, the mean for these two cases lies between 09:17 and 09:03 minutes.

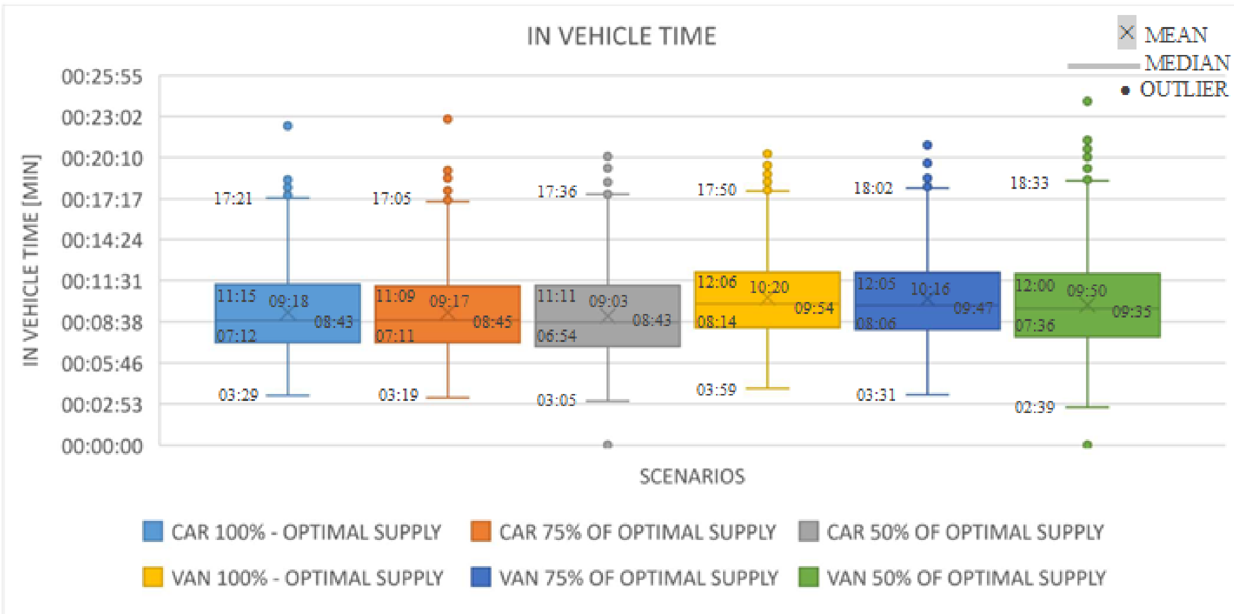

Figure 14: In-vehicle time of ODT (detour factor 1.5). The 'x' marks the mean of the in-vehicle travel time. The horizontal line represents the median of the in-vehicle travel time. The vertical line (whiskers) is the variability of the in-vehicle travel times outside Q1 and Q3. The dots outside the whiskers are the data outliers

The in-vehicle times for car-based trips have about the same duration at each supply level, which means that the level of service regarding in-vehicle time remains the same. But in the lowest supply case, more passengers end up not being picked up, which worsens the service quality and makes it less reliable.

The results for the van-based trips as the car-based trips show a slight increase of in-vehicle time with a decrease of available vehicles. For the *optimal supply*, travellers spend on average 10:20 minutes in the vehicle, whereas 10:16 minutes for 75% of *optimal supply* and 09:50 minutes for 50% of *optimal supply* are needed. Most requesters picked up with optimal fleet size need 08:14 to 12:06 minutes till they reach their destination. In-vehicle times are stretched out from 08:06 to 12:05 minutes for the 75% of the *optimal supply* case, and 07:36 to 12:00 minutes for 50% of *optimal supply*. In general, the results are lower dispersed for the van-based scenarios.

The origin wait time at the PUDO has a high influence on the total travel time and the passenger's mode choice. The results with a detour factor of 1.5 are shown in Figure 15, where increasing wait time is detected with a decrease in available vehicles. Interesting to note is the slightly shorter wait times for van-based trips due to the vehicles (vans or cars) picking up requests which are close to each other. As vans can serve more passengers, the wait time decreases a little bit when compared to car-based trips. As stated in Section 4.3, the wait times are restricted to a maximum of 15 minutes.

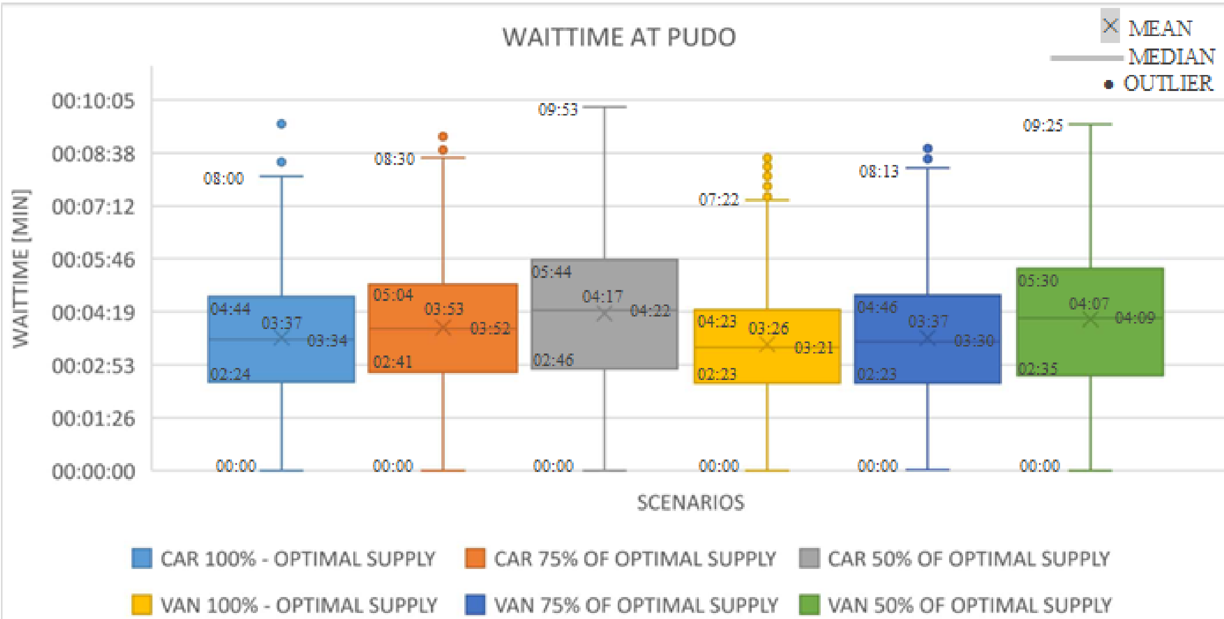

Figure 15: Wait time of ODT (detour factor 1.5) at origin. The 'x' marks the mean of the waiting times. The horizontal line represents the median of the waiting times. The vertical line (whiskers) is the variability of the waiting times outside Q1 and Q3. The dots outside the whiskers are the data outliers

The first quartile of the car-based case with *optimal supply* has a very low wait time, which lies between 0 and 02:24 minutes. That means 25% of all served requests are picked up within two minutes wait time. Half of all trip requesters have to calculate their journey with a wait time between 02:24 minutes and 04:44 minutes. The last quartile has a higher dispersion and the wait time is in the range of 04:44 minutes to 8 minutes. Mean and median are almost equal with about 3.5 minutes. If only 75% of cars are available, the wait time increases about 20 seconds in mean and median. For the case with 50% of *optimal supply*, another 25 to 30 seconds are added to mean and median. The variance of quartile two and three is slightly higher and reaches from 02:46 to 05:44 minutes.

Like the car-based scenarios, the van-based situations show a slightly increasing wait time with decreasing vehicle numbers. The mean wait time of the van-based scenario with *optimal supply* is with 03:26 minutes shorter than the car-based counterpart. Additionally, the variance is smaller and half of all trip requesters have to wait between 02:23 minutes to 04:23 minutes at the PUDO. In the case with 50% of *optimal supply*, requesters have to plan with a mean wait time of 04:07 minutes. The interquartile range has a minimum of 0 minutes and a maximum of 9:53 minutes. The wait time slightly rises for the cases with 75% and 50% of *optimal supply*, but also the number of unserved requests is increasing, which explains the growth in wait time.

5.1. Detour factor of 5

Demand satisfaction, in-vehicle time and wait time are highly influenced by the detour factor. To examine the effect in more details, another simulation is run with an increased factor of five and a maximum detour time of 60 minutes. The same fleet sizes as for the scenario with 1.5 detour factor are used for better comparison.

Comparing the results of detour factor 1.5 and 5, it can be said that for the case with 75% of *optimal supply*, the number of unserved requests decreases with 1% for cars and 4% for vans. For the scenario with 50% of *optimal supply*, the unserved requests decrease from 27% to 26% for cars and fall from 32% to 25% for vans. The increase of the detour factor has a strong effect when it comes to the number of served trips, especially for the van-based scenario with 50% of *optimal supply*–results can be seen in Figure 16.

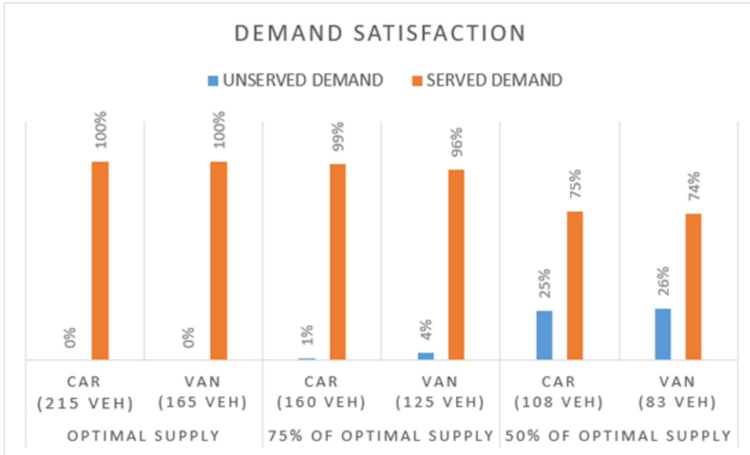

Figure 16: Demand satisfaction ODT (detour factor 5)

Like in the scenario with 1.5 detour factor, the total of full vehicles (vans or cars) decreases for all supply states when fewer vehicles are available. Remarkably the scenario with 5 detour factor states a higher number of fully occupied vehicles. With a higher detour factor, more passengers can be picked up with one vehicle. The trend for not fully occupied vehicles is the same for cars and vans–both cases show a very low number of trips that are not fully occupied (Figure 17).

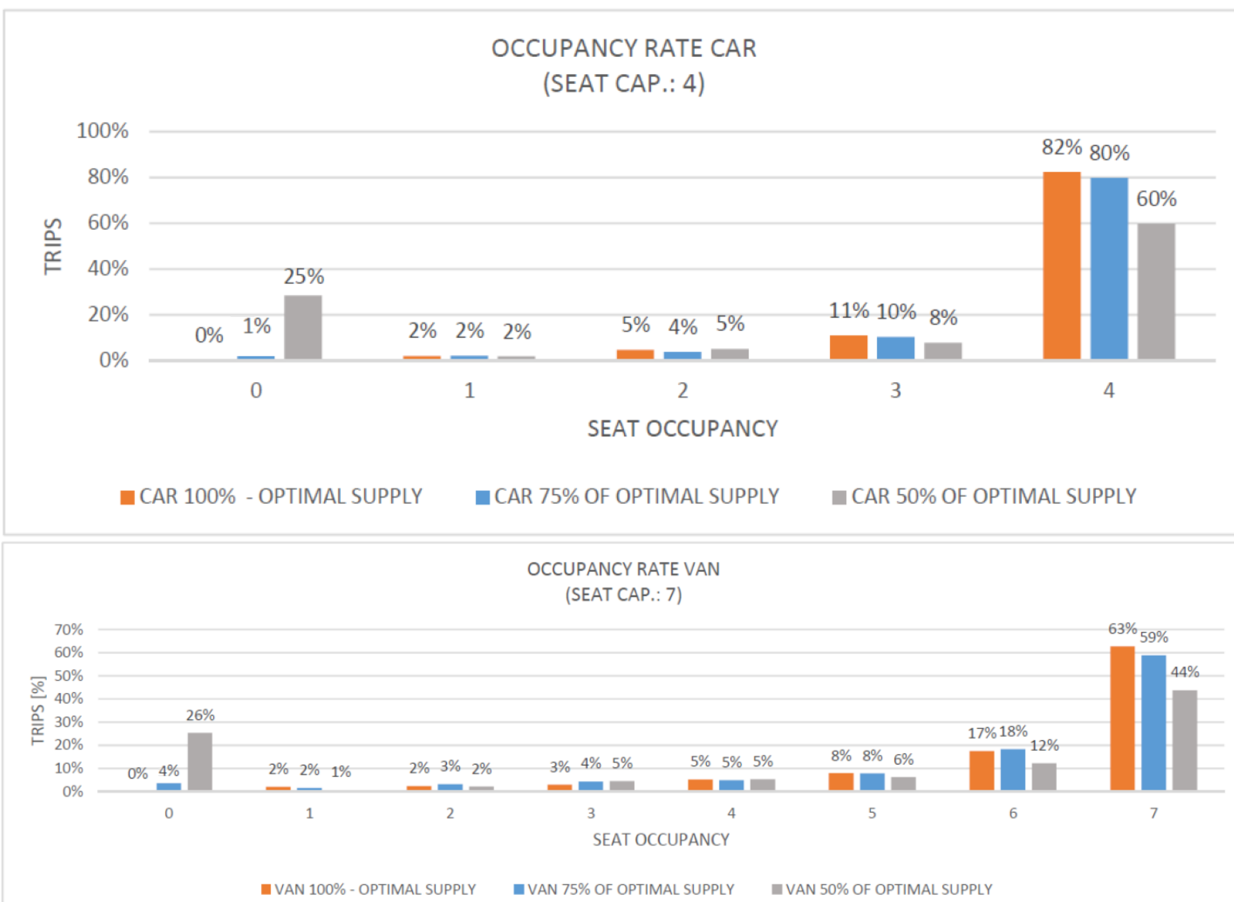

Figure 17: Occupancy Rate ODT (detour factor 5)

The in-vehicle time with 5 detour factors is presented in Figure 18. It is directly noticeable that this scenario produces a large number of outliers above the maximum value. Because of the high detour factor, trips with high in-vehicle times are possible. Whereas in the scenario with 1.5 detour factor, longer in-vehicle times are not. Generally, the trend of mean in-vehicle time is decreasing with smaller fleet sizes. Comparing van and car-based scenarios, it is clearly visible that vans are about 01:30 minutes slower. Looking at the second and third quartile, the dispersion of in-vehicle times is smaller for car-based scenarios than for van-based scenarios (7 minutes for cars vs. 8 minutes for vans). This effect is understandable with the different tour lengths for both vehicles. Since vans have a higher seat capacity, more passengers are picked up, a single tour can serve more requests. In general, the in-vehicle time does not differ by much when testing different fleet sizes. Car-based trips take about 11:30 minutes, whereas trips operated by van have an average duration of about 13:00 minutes.

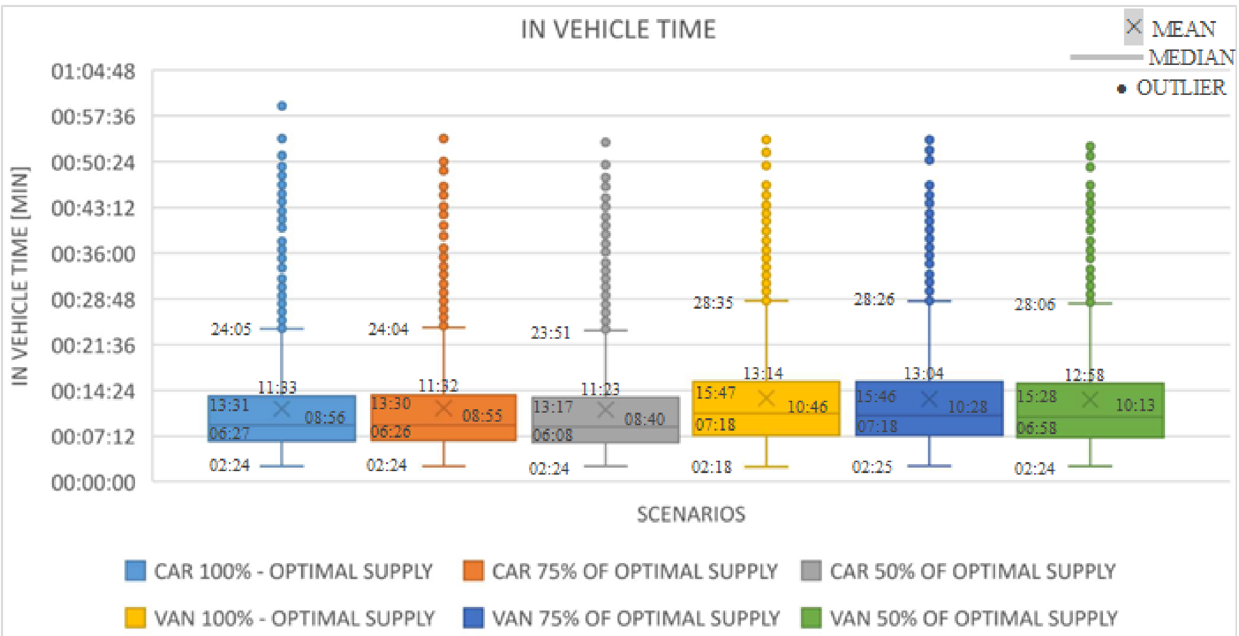

Figure 18: In-vehicle Time of ODT (detour factor 5). The 'x' marks the mean of the in-vehicle travel time. The horizontal line represents the median of the in-vehicle travel time. The vertical line (whiskers) is the variability of the in-vehicle travel times outside Q1 and Q3. The dots outside the whiskers are the data outliers

In addition to the in-vehicle time, the origin wait time is analyzed and shown in Figure 19. The origin wait time of passengers at the pick-up point is increasingly developing with decreasing available vehicles. The first quartile of the car-based case with *optimal supply* has a very low wait time, which lies between 0 and 01:06 minutes. That means 25% of all served requests are picked up within a minute wait time. Half of all trip requesters have to calculate their journey with a wait time between 01:06 minutes and 09:34 minutes. The last quartile wait time is in the range of 09:34 minutes and 15 minutes. The mean wait time is 05:39 minutes, which is about 40 seconds longer than the median (04:57 minutes). If only 75% of all cars are available, the mean wait time increases about 10 to 20 seconds in mean and median, respectively. For the case with 50% of *optimal supply*, another minute is added to the mean and 1.5 minutes to the median. The variance of quartile two and three is slightly higher than for 100% of *optimal supply* and 75% of *optimal supply* and reaches from 2:23 to 11:06 minutes. For all car-based cases, the minimum wait time is zero minutes and the maximum wait time sums up to 15 minutes.

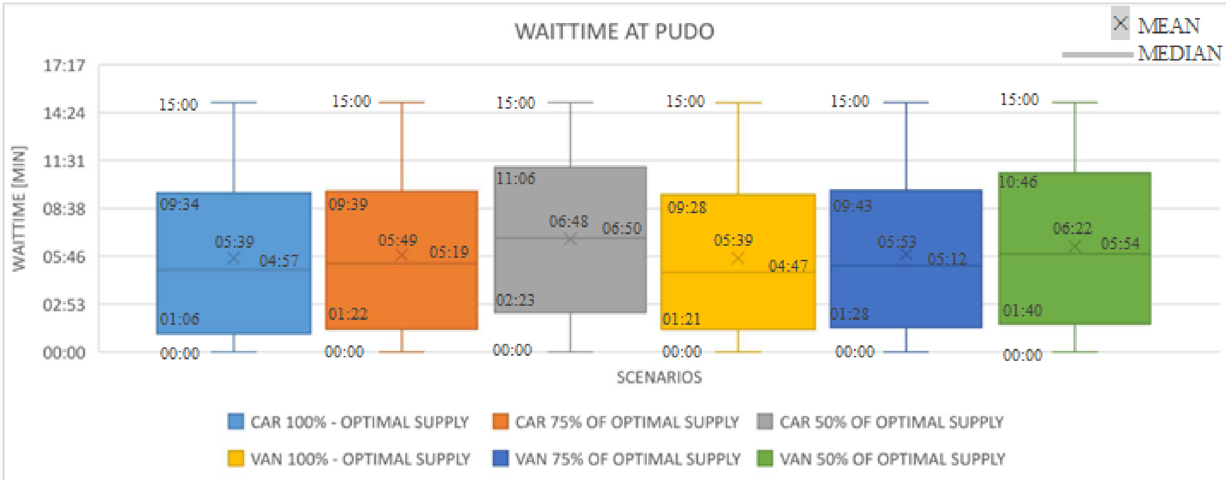

Figure 19: Wait time at origin ODT (detour factor 5). The 'x' marks the mean of the waiting times. The horizontal line represents the median of the waiting times. The vertical line (whiskers) is the variability of the waiting times outside Q1 and Q3

Like the car-based scenario, the van-based shows a slightly increasing wait time with decreasing fleet. The mean wait time of the van-based scenario with *optimal supply* is 05:39 minutes, which is the same as the car-based counterpart. Half of all trip requesters have to wait between 01:21 minutes to 09:28 minutes at the PUDO. In the case with 75% of *optimal supply*, requesters have to plan with a mean wait time of 05:53 minutes. The range of second and third quartiles reaches from 01:28 minutes to 09:43 minutes. The wait time slightly rises for the case with 50% of *optimal supply* and the mean is stated with 06:22 minutes. Half of all requesters have to wait between 01:40 minutes and 10:46 minutes, whereas the median wait time is 05:54 minutes. The interquartile range has a minimum of 0 minutes and a maximum of 15 minutes for all van-based scenarios. It can be concluded that the stronger the increase of unserved requests, the higher the increase in wait time. And as expected, small fleets impact negatively on the wait time.

5.2. Cost analysis of the ODT system

To compute an approximate vehicle cost, the vehicle kilometres travelled are multiplied by 0.50CAD/km for cars and 0.65CAD/km for vans[4], these costs include depreciation, financing, insurance, maintenance, and fuel (Government of Canada, 2021). Driver cost is estimated by multiplying the total drivers by the minimum wage per hour, in 2018 the general minimum wage in Ontario, Canada was 15CAD[5] per hour (Ministry of Labour, Training and Skills Development, 2021). The cost of unserved request is also incorporated in the analysis to account for the users that are not served on each time-slice. It is assumed that if a request is not served in a time-slice, at an average it will cost the user 15 minutes of their time. According to Statistics Canada (2018) in 2018 the value of time for Canadians was 25CAD per hour, hence 15 minutes are valuated in 6.25CAD. Therefore, each unserved request adds 6.25CAD to the total cost of the ODT.

Detailed results are shown in Table 2. The cheapest scenario is the van-based at 75% of *optimal supply* and a detour factor of 5 with a total cost of 9, 776CAD. Due to a higher seat capacity, fewer drivers and a low number of unserved request, the cost is low. Additionally, fewer kilometres are travelled in total due to the high detour factor. The van-based scenario at *optimal supply* and a detour factor of 5 is following with a cost of 10, 864CAD. After, the van-based scenario with 75% of *optimal supply* and a detour factor of 1.5 states the third most economical option. From this analysis it is concluded that the car is not a good option for the ODT system as car scenarios tend to have a higher cost when comparing to the van scenarios.

[4]According to the Government of Canada (2021) in 2018, the vehicle cost per kilometre was 55¢ for the first 5,000 kilometres driven and 49¢ per kilometre driven after that. Since there is no desegregated data for cars and vans, the cost is set at 0.50CAD/km for cars and 0.65CAD/km for vans.

[5]According to the Ministry of Labour, Training and Skills Development (2021) of Ontario, in 2018 the general minimum wage in Ontario was 14CAD, but in practice most of the employers in the GTA pay at least 15CAD per hour.

Table 2: Cost analysis of Approach A and B

Scenario		Mode	Fleet size [vhe]	Unserved demand [%]	Kilometres travelled [km]	Drivers needed [pers]	Wage/3h [CAD]	Cost unserved request [CAD]	Driver cost [CAD]	Cost/km [CAD]	Vehicle cost [CAD	Cost/served request [CAD]	Total cost [CAD]
Detour factor 1.5	**Optimal supply**	**Car**	215	0%	7826	215	45	0	9675	0.50	3913	7.29	13588
	75% optimal supply		160	5%	7705	160		1579.2	7200		3852.50	6.21	12631.72
	50% optimal supply		108	22%	5746	108		7621.1	4860		2873	5.32	15354.14
	Optimal supply	**Van**	165	0%	6025	165		0	7425	0.65	3916.25	6.08	11341.25
	75% optimal supply		125	5%	5961	125		1850.4	5625		3874.65	5.38	11350.13
	50% optimal supply		83	32%	4491	83		11143.7	3735		2919.15	5.26	17797.89
Detour factor 5	**Optimal supply**	**Car**	215	0%	7615	215		0	9675	0.50	3807.50	7.23	13482.50
	75% optimal supply		160	4%	7805	160		1412	7200		3902.50	6.21	12514.51
	50% optimal supply		108	26%	6000	108		8899.3	4860		3000	5.67	16759.38
	Optimal supply	**Van**	165	0%	5292	165		0	7425	0.65	3439.80	5.83	10864.80
	75% optimal supply		125	1%	5673	125		464.4	5625		3687.45	5.06	9776.93
	50% optimal supply		83	25%	4343	83		8787.9	3735		2822.95	4.71	15345.86

Table 3 shows a comparative analysis of the scenarios. Not all scenarios can be compared equally because the result types may vary. The evaluation scale reaches from three minuses (very bad) to three pluses (very good). Zero means that the result is in the middle of the range. The results are evaluated and summed up in the last column. In-vehicle time and wait time are represented with the mean-time for each case. The total cost accounts for the cost of drivers, vehicles and, unserved demand.

Three scenarios have better results when considering the fleet size, unserved demand, total travel time, cost per served request and total cost. The van-based scenario, with *optimal supply* and detour factor of 5 (marked with an 'A'), gives good results in terms of cost and is similar to the van-based scenario with 75% and detour factor of 5 (marked with 'B'). The scenario with 75% of *optimal supply* using vans and 1.5 detour factors (marked with 'B') shows has higher cost but has the lowest in-vehicle travel time and wait time.

If price is the most important characteristic, scenario 'A' is the choice. The weakness for scenario 'A' lies in the longest wait times, when compared to scenarios 'B' and 'C'. If the service quality with regard to unserved trips has a higher importance, scenario 'B' states the best option, but this scenario has the longest in-vehicle time and the second largest wait times when compared with scenario 'A' and 'C'. Scenario 'C' presents the lowest in-vehicle and wait times, and the cost difference from the other scenarios is less that 2,000CAD. For an ODT implementation in Markham the scenario 'C' is the better option as it has a good balance regarding total travel time (in-vehicle time plus wait time) and cost. Scenario 'A' is the most expensive, however, this scenario will bring to the users a better level of service. This scenario is the fastest and can save the users up to 5mins, when compared to scenarios 'A' and 'B'. This 5mins can be the difference between arriving at the train station on time or missing the train and waiting for another 15min for the next train. Given the limitation of *MaaS Modeller*, currently we do not have the capacity to evaluate exactly which request will arrive on time for the trains.

5.3. Cost of ODT versus private car

Table 4 shows the cost comparison of Scenario 'C' versus using private cars with and without parking fees. For making the comparison, the following scenarios are considered:

Table 3: Comparative analysis

	Scenario	Mode	Fleet-size [veh]		Unserved demand [%]		Mean in-veh time [min]		Mean Wait Time [min]		Cost/served request [CAD]		Total Cost [CAD]		Result
Detour factor 1.5	Optimal Supply	Car	215	− − −	0%	+ + +	09:18	++	03:37	+	7.29	− − −	13588	+	+
	75% optimal supply		160	0	5%	+	09:17	++	03:53	0	6.21	−−	12631.72	+	++
	50% optimal supply		108	++	22%	-	09:03	+++	04:17	− − −	5.32	++	15354.14	-	++
	Optimal supply	Van	165	0	0%	+++	10:20	− − −	03:26	+++	6.08	0	11341.25	++	+++++
	75% optimal supply		125	++	5%	+	10:16	−−	03:37	++	5.38	++	11350.13	++	+++++++(C)
	50% optimal supply		83	+++	32%	− − −	09:50	0	04:07	-	5.26	++	17797.89	− − −	−−
Detour factor 5	Optimal Supply	Car	215	− − −	0%	+++	11:33	+++	05:39	+++	7.23	− − −	13482.50	+	++++
	75% optimal supply		160	0	4%	+	11:39	++	05:49	++	6.21	-	12514.51	+	+++++
	50% optimal supply		108	++	26%	−−	11:23	+++	06:48	− − −	5.67	+	16759.38	−−	−
	Optimal Supply	Van	165	0	0%	+++	13:14	− − −	05:39	+++	5.83	+	10864.80	+++	+++++++(B)
	75% optimal supply		125	++	1%	++	13:04	−−	05:53	+	5.06	++	9776.93	+++	++++++++(A)
	50% optimal supply		83	+++	25%	−−	12:58	-	06:22	0	4.71	+++	15345.86	−	++

1. **Free parking at the GO Transit stations:** one scenario considers a single occupancy trip (just the driver), while the other considers a double occupancy trip such that the passenger and driver split the cost.

2. **Reserved parking at GO Transit stations:** one scenario considers a single occupancy trip, while the other considers a double occupancy trip such that the passenger and the driver split the cost.

3. **Single request to the ODT system:** one scenario considers a single occupancy request, while the other considers a double occupancy request where both requester split the cost.

Table 4: Private vehicle versus ODT cost

	Cost (km)	**Cost (trip)**	**Parking cost (day)**	**Driver cost per trip**	**Booking fee**	**Wait time cost (min)**	**Trip total cost**	**Monthly cost**
Free parking								
Single occupancy	0.5	2.15	0	0	0	0	2.15	368.2
Double occupancy	0.25	1.07	0	0	0	0	1.07	325.2
Have a reserved parking spot								
Single occupancy	0.5	2.15	4.90	0	0	0	7.05	564.2
Double occupancy	0.25	1.07	2.45	0	0	0	3.52	423.2
ODT system scenario ‘C’								
Request single occupancy	0.65	2.79	0	2.53	1.75	1.45	8.53	585.9
Request double occupancy	0.325	1.38	0	1.26	0.87	1.45	4.99	460.5

According to TTS (2016) data, in Markham the average trip length is 4.8km. Based on the data from the Government of Canada (2021), we assumed an average cost per kilometre of 0.50CAD for private trips and 0.65CAD for the ODT system. Parking at the GO Transit stations is limited, but free based on the availability. However, it is possible to reserve a parking spot from 98CAD per month (Go Transit, 2021). Reserved parking lets users rent a parking space for use, Monday to Friday so the daily cost of the parking spot is 4.90CAD. As shown in Table 2 and Table 3, the wage per hour of drivers is 15CAD and the average trip is 10:00min, then the average cost of ODT drivers is 2.53CAD per trip. Most on-demand transport services charge a fee for booking, let assume the booking fee of the ODT is 1.75CAD (the current *Uberpool* booking fee for Ontario). The personal valuation of time is an important point to consider as the ODT users will have to wait at the pick-up points, according to Statistics Canada (2018) in 2018 the value of time for Canadians was 25CAD per hour. If the average wait time of scenario 'C' is 3:37min then the average wait time cost of request is 1.2CAD.

Considering only the total cost, the cheapest mobility option is the private car as long as the driver gets a free parking spot. However, the parking spots are limited and free parking is not guaranteed. As shown in Table 4 the cost per trip of the ODT and the private trip with reserved parking spot differ by less than one dollar. If the cost per trip is considered only, the ODT might not be too attractive to the users. The proposed ODT is designed for first-mile trips, so recurrent users committing daily are expected. Let us consider the monthly cost of commuting (first-mile trip plus the GO Transit trip) of an average markhamite. The fare from the GO Transit to downtown Toronto is 7.91CAD for the first 35 trips and 1.07 for the next 5 trips. If a normal user makes 40 trips in a month, the monthly cost of the GO Transit is 282.2CAD, hence, recurrent users have an 11% reduction compared to the cost of 40 trips at 7.91CAD. Therefore, the cost of a commuter with a private vehicle with free parking is 368.2CAD a month, 86CAD for 40 trips plus 282.2CAD for the GO Transit. While the users with a reserved parking spot pay 564.2CAD a month, 86CAD for 40 trips, plus 98CAD for parking all weekdays, plus 282.2CAD for the GO Transit. Let assume that ODT users also save 11% of the cost if they make 40 trips in a month, hence single occupancy ODT users will pay 585.9CAD a month, 303.7CAD for 40 ODT trips plus 282.2CAD for the GO Transit. Whereas the cost per month for double trips would be 460.05CAD, 177.85CAD for 40 ODT trips plus 282.2CAD for the GO Transit. In terms of cost, the ODT might not be too attractive for users with private vehicles and reserved parking spots, they would expect an increase of 4% for a single and 9% for double occupancy trip. The increase in the cost is not too high for single occupancy trip and taking into account that these users will eliminate the need to drive and could use the in-vehicle time in the ODT for other activities, this type of user could be persuaded to shift from using the private vehicle to use the ODT. Furthermore, due to the land demand the Government of Ontario is planning to drastically reduce the free park spots at GO Transit stations (Jeffords, 2021). Once the policy is implemented, it will make the ODT implementation in Markham more attractive. Note that most of the public transit systems in Canada are subsidized by federal and provincial governments. Considering that ODT has the potential to reduce emissions in the city (see Section 5.4), the government may subsidize the ODT service by covering the booking cost of 1.75CAD per trip. This will reduce the trip cost of the ODT system and make it financially more attractive for the commuters by 7%.

5.4. GHG reduction

Considering Scenario 'C', a GHG comparison with the base-case will be presented. In Ontario, one of the best selling vehicles is the *Honda Civic* (Automatic, 1.8L, 4 cylinders) (Cain, 2019). Since not all cars on Markham's streets are brand new or too old, and in general, the Markamites are upper-middle-class, let us assume that 2015 is the average year of make for the vehicles. Based on that, we consider that the $1,865$ private vehicles of the base-case are 2015 *Honda Civic*. For Scenario 'C', let us assume that the fleet is composed of 2015 *Toyota Sienna* (Automatic-AS8, 3.5L, 6 cylinders). Toyota is a popular brand among *Uber* drivers in North America (Statista, 2018) and the price of the *Sienna* is mid-range among the vehicles of its class, so it is fair to assume that this vehicle would be popular in an ODT service. Considering the fleet size and vehicle-kilometers traveled in both scenarios (base-case and Scenario 'C'), the total CO_2[6] emissions per year are presented in Table 5.

Table 5: GHG count per year

Scenario	**Vehicle Type**	**Year**	**Kilometres Travelled [km]**	**Fleet size [veh]**	**Kilometres per vehicle [km]**	**Workdays**	**CO_2 per vehicle [tons]**	**CO_2 fleet [tons]**
Base case	*Honda Civic*	2015	9325	1865	5	250	0.3	559.5
Scenario C	*Toyota Sienna*	2017	5691	125	47.68	250	3.133	391.625

[6] CO_2 is computed using the online calculator available at https://www.offsetters.ca/education/calculators/car-emissions-calculator

For the assumptions presented in the above paragraph, a 30% reduction CO_2 tons per year is expected if Scenario 'C' is implemented, substituting all private trips from any point in Markham to the GO rail stops presented in Section 3.1. It is worth noting that the CO_2 computation is a rough estimate and does not consider parameters such as driving behaviour or traffic conditions. A comprehensive CO_2 emission computation is out of the scope of this paper, but the intentions of the authors are to show that CO_2 savings are possible if on-demand transit is implemented in Markham.

6. Conclusions and future work

This study presents a detailed analysis for improving the first-mile transportation in Markham. A simulation using *PTV MaaS Modeller* and *Visum* is created to model an ODT service with two main types of vehicles, i.e. four-seater vehicles (car) or the seven-seater vehicles (van). For each type of vehicle, three scenarios are developed based on different fleet sizes, seat capacities, detour factors and maximum detour time. The *optimal supply* is computed and based on the size of this supply, cases with 75% and 50% availability of *optimal supply* are created and examined regarding travel and wait time. During the analysis, it became clear that another simulation with a deviation on the detour factor had to be developed to get a better overview of the range and impact of detour factors.

Cases are rated based on the cost and benefits by comparing fleet size, total drivers, driven kilometres and the length of wait and travel time. Considering the cost, served demand, and wait times, the best strategy for Markham (scenario 'C') is to implement an ODT service consisting of 125 seven-seat vehicles (vans) for serving the first-mile demand in the morning peak hour. In terms of waiting time (around 3 minutes), scenario 'C' is consistent with the results found by Kamau et al. (2016). A large fleet size is not economically viable, as such an optimal fleet size is required to allow efficient operations. The fleet size of scenario 'C' is within the limits found by Becker et al. (2020), which corroborate the presented results. Although the fleet size of scenario 'C' is not the most economical solution, it has the right balance regarding unserved demand and total travel time.

Although most of the households in Markham own at least one car, the ODT might be marketed as a substitute for a second vehicle with a pay-as-you-go subscription, as pointed out by Ho et al. (2020). In Markham, less than 10% of the trips are made by transit, walk, or bike. This mode share is very low compared to the 43% share in the City of Toronto (Ashby, 2016). Investigating the reasons behind markhamites' high dependency on cars is out of the scope of this study, but the fact of the matter is that they prefer cars. Given the similarities between personal cars and the ODT (e.g. almost door-to-door service, easy to request, comfort, similar cost, etc.) markhamites could be convinced to use the ODT service. If the monthly GO Transit fare is integrated with the ODT fare (40 trips per month), user might expect a 5% savings when compared with the users that nowadays pay fees for reserving a parking spot at the train stations. Such integration has already been tested for the Go Transit and Toronto's local transit. The ODT service has the potential to reduce GHG emissions and congestion, so subsidizing the ODT system is an attractive idea. It is expected that given the poor usage of transit and high demand to reach the GO Transit, residents of Markham are more likely to accept the ODT than the residents living in downtown, as also pointed out by Jain et al. (2017).

This study only considered a homogeneous fleet, but the cost of the overall system might be further reduced if a carefully optimized heterogeneous fleet is considered. As shown in Figure 5, the western part of Markham has more trips to the GO Transit stations than the eastern part. In future research, it might be a good idea to try exploring how the ODT system performs when the western part is served by vans and the eastern part by cars. Since the demand for different train stations varies, different sizes of vehicles might improve the ODT system's overall cost, for instance, stations with low demand can be served by cars and the high demand stations with vans. In the *MaaS Modeller* version used for this simulation, it is currently not possible to set a heterogeneous fleet. In future studies, it would be interesting to optimize the heterogeneous fleet and analyze the effects with appropriate tools.

To achieve a better performance in terms of the fleet size and waiting times, it is worth exploring the repositioning of empty vehicles (rebalancing). Ruch et al. (2018) simulated an ODT system with rebalancing policies and found a significant reduction in the waiting times for certain demand and fleet size scenarios. In the simulation proposed by Hörl et al. (2019), it was found that with a proper rebalancing algorithm it is possible to reduce the fleet size and waiting times when compared with an ODT with no rebalancing setting. As mentioned in the previous paragraph, it is expected that the ODT will bring savings to the users with reserved parking spots considering the fleet size of scenario 'A'. If this fleet is reduced even further by implementing rebalancing algorithms the user savings will be increased, so rebalancing techniques should be further explored in future. research.

Since *MaaS Modeller* is a proprietary software, the TSP variation for dispatching vehicles is not publicly disclosed, so it is safe to assume this work presents a lower bound on the efficiency of the proposed ODT system for Markham. Although the TPS can be used for improving the efficiency of the on-demand ride-share services, other techniques like the shareability graph presented by Alonso-Mora et al. (2017) were able to find optimal solutions for these type of transit systems.

Another problem associated with the ODT system is the parking of the fleet during out-of-service hours. A depot for storing the ODT fleet is out of the question, since this depot probably will take a space that could be used for more beneficial ends like parks, housing or sport fields. The fleet size of scenario 'A' comprises of 125 vehicles, so it is possible to accommodate the fleet at the station parking lots during the night, when the demand for parking is low. Since there are 3817 parking spots at the three stations, the ODT fleet will only take 3% of the spots, so parking the fleet in low demand parking hours might work. Another possibility for accommodating the fleet during the out-of-service hours is to crowdsource the vehicles like Uber, where the drivers will park the vehicles at home and reduce needs of centralized parking depots for the ODT fleet.

In summary, a successful implementation of an ODT system needs to take the following points into account. The list is not intended to be exhaustive, but reflects the findings of the research:

- Grid-structured urban areas (like the 'classic' North-American suburbs) that lead to long walking distances for accessing transit stops are ideal for implementing the ODT system, as the ubiquitousness of the stops will reduce the walking distance, while on-demand booking service will mitigate the waiting times
- ODT system is better suited than fixed route transit for the adoption by the population with high dependency of private vehicles and in areas where the destination has few free parking spots
- Dense urban areas where the share of transit is large (e.g. downtown Toronto), are not ideal for an ODT system since transit is much frequent
- The cost related to the unserved requests, fleet size and composition are a large share of the ODT system's overall cost. The operational costs are not considered in this research, but they are expected to be smaller. Hence, for making the ODT system more competitive with private vehicles, the fleet size and relocation have to be carefully tuned
- Fleets composed only of 4 seater-vehicles are expensive and probably not economically viable
- Use of heterogeneous fleet can be explored to account for spatial heterogeneity in demand
- For the case of an ODT system for first-mile trips, the space for parking the ODT vehicles (during service hours and out-of-service hours) have to be taken into account

In terms of future work, other factors are of interest that will help to identify potential issues in specific traffic analysis zones. For instance, it would be interesting to compute the distribution of detour factors and wait times per zone to know if there are outliers in certain zones and see if by changing the location of pick-up points the ouliers can be reduced. We would like to explore how the unserved trip requests are spatially distributed. This will help to identify possible reasons like road geometry, time of the request, or other factors that impact negatively. Other interesting point is the cost analysis in term of users and sociodemographics with the maximum detour factor and wait time. It is possible that such users could save the most if they shift from private vehicles to an ODT, so targeting such population into using the ODT system will have more impact than those whose detour factor and wait time are lower. Other factor to consider is how the maximum wait time and train arrivals are related. As mentioned earlier, the main reason behind choosing the 15mins slice is that trains arrive at GO Transit stations every 15mins. Selecting shorter or longer time-slices will cause users to either wait too long at the stations or will cause the user to miss their train. However, it is worth considering how the ODT system is impacted, if the 15mins time window changes or to measure how many of the requests get to the train on time if the maximum wait time changes. The future application of advanced matching algorithms e.g. the graph based many-to-one matching algorithm proposed by Meshkani and Farooq (2021) might bring some light to answering the questions presented here. To the best of our knowledge the questions presented here are not addressed in the previous literature on real case studies and are worth considering. The role of automated, connected, and electric vehicles in improving the proposed on-demand transit system will also be explored. Furthermore it is important to look at an overarching level to understand how the implementation of an ODT system depends on collaboration between citizens, customers and users over regional and local governments as well as public and private service providers up to the national government (Karlsson et al., 2020).

Acknowledgments

We are thankful to *PTV Group* for its support of the project and providing us with the necessary software and expertise. This research was funded by the Canada Research Chair in Disruptive Transportation Technology and Services.

References

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences 114, 462–467. URL: https://doi.org/10.1073/pnas.1611675114, doi:10.1073/pnas.1611675114.

Archetti, C., Speranza, M.G., Weyland, D., 2017. A simulation study of an on-demand transportation system. International Transactions in Operational Research 25, 1137–1161. doi:10.1111/itor.12476.

Ashby, B., 2016. Transportation Tommorrow Survey 2016. Technical Report. Malatest.

Batarce, M., Muñoz, J.C., Ortúzar, J.d.D., Raveau, S., Mojica, C., Ríos, R.A., 2015. Evaluation of Passenger Comfort in Bus Rapid Transit Systems. Technical Report IDB-TN-770. Inter-American Development Bank.

Becker, H., Balac, M., Ciari, F., Axhausen, K.W., 2020. Assessing the welfare impacts of shared mobility and mobility as a service (MaaS). Transportation Research Part A: Policy and Practice 131, 228–243. doi:10.1016/j.tra.2019.09.027.

Bian, Z., Liu, X., 2017. Planning the ridesharing route for the first-mile service linking to railway passenger transportation, in: 2017 Joint Rail Conference, American Society of Mechanical Engineers. p. 11. doi:10.1115/jrc2017-2251.

Cain, T., 2019. Canada's 10 best-selling automakers in 2018. URL: https://driving.ca/ford/auto-news/news/canadas-10-best-selling-automakers-in-2018.

Cayford, R., Yim, Y., 2004. Personalized Demand-Responsive Transit Service. Technical Report UCB-ITS-PRR-2004-12. California PATH Program.

Cervero, R., 1993. Surviving in the suburbs: Transit's untapped frontier. ACCESS 2, 29–34.

Chen, S., Wang, H., Meng, Q., 2019. Solving the first-mile ridesharing problem using autonomous vehicles. Computer-Aided Civil and Infrastructure Engineering 35, 45–60. doi:10.1111/mice.12461.

Daganzo, C.F., Ouyang, Y., 2019. A general model of demand-responsive transportation services: From taxi to ridesharing to dial-a-ride. Transportation Research Part B: Methodological 126, 213–224. doi:10.1016/j.trb.2019.06.001.

Djavadian, S., Chow, J.Y., 2017. An agent-based day-to-day adjustment process for modeling 'mobility as a service' with a two-sided flexible transport market. Transportation Research Part B: Methodological 104, 36–57. doi:10.1016/j.trb.2017.06.015.

D'Incà, J., Mentz, C., 2016. What the future of mobility means for today's transportation industry. URL: https://www.forbes.com/sites/oliverwyman/2016/11/17/what-the-future-of-mobility-means-for-todays-transportation-industry/#4b8cce6822d4.

European Platform on Mobility Management, 2019. Update december. URL: http://www.epomm.eu/newsletter/v2/eupdate.php?nl=1217_2&lan=en.

Franco, P., Johnston, R., McCormick, E., 2020. Demand responsive transport: Generation of activity patterns from mobile phone network data to support the operation of new mobility services. Transportation Research Part A: Policy and Practice 131, 244–266. doi:10.1016/j.tra.2019.09.038.

Frei, C., Hyland, M., Mahmassani, H.S., 2017. Flexing service schedules: Assessing the potential for demand-adaptive hybrid transit via a stated preference approach. Transportation Research Part C: Emerging Technologies 76, 71–89. doi:10.1016/j.trc.2016.12.017.

Furuhata, M., Dessouky, M., Ordóñez, F., Brunet, M.E., Wang, X., Koenig, S., 2013. Ridesharing: The state-of-the-art and future directions. Transportation Research Part B: Methodological 57, 28–46. doi:10.1016/j.trb.2013.08.012.

Go Transit, 2021. Your fare. URL: https://www.gotransit.com/en/trip-planning/calculate-fare/your-fare.

González, M.J.A., van Oort, N., Cats, O., Hoogendoorn, S.P., 2017. Urban demand responsive transport in the mobility as a service ecosystem: Its role and potential market share, in: International Conference Series on Competition and Ownership in Land Passenger Transport 2017, p. 18.

Gotransit, 2019. Go transit — regional public transit service for the gtha. URL: https://www.gotransit.com.

Government of Canada, 2021. Automobile allowance rates. URL: https://www.canada.ca/en/revenue-agency/services/tax/businesses/topics/payroll/benefits-allowances/automobile/automobile-motor-vehicle-allowances/automobile-allowance-rates.html.

Ho, C.Q., Mulley, C., Hensher, D.A., 2020. Public preferences for mobility as a service: Insights from stated preference surveys. Transportation Research Part A: Policy and Practice 131, 70–90. doi:10.1016/j.tra.2019.09.031.

Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K., 2019. Fleet operational policies for automated mobility: A simulation assessment for zurich. Transportation Research Part C: Emerging Technologies 102, 20–31. doi:10.1016/j.trc.2019.02.020.

Jain, S., Ronald, N., Thompson, R., Winter, S., 2017. Predicting susceptibility to use demand responsive transport using demographic and trip characteristics of the population. Travel Behaviour and Society 6, 44–56. doi:10.1016/j.tbs.2016.06.001.

Jeffords, S., 2021. Metrolinx considers paid parking for go transit station lots. URL: https://globalnews.ca/news/6409884/metrolinx-considers-paid-parking-go-transit-lots/.

Jetty, 2019. How it works. URL: https://www.jetty.mx/.

de Jong, W., Vogels, J., van Wijk, K., Cazemier, O., 2011. The key factors for providing successful public transport in low-density areas in the netherlands. Research in Transportation Business & Management 2, 65–73. doi:10.1016/j.rtbm.2011.07.002.

Kamau, J., Ahmed, A., Rebeiro-H, A., Kitaoka, H., Okajima, H., Ripon, Z.H., 2016. Demand responsive mobility as a service, in: 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE. pp. 001741–001746. doi:10.1109/smc.2016.7844489.

Karlsson, I., Mukhtar-Landgren, D., Smith, G., Koglin, T., Kronsell, A., Lund, E., Sarasini, S., Sochor, J., 2020. Development and implementation of mobility-as-a-service – a qualitative study of barriers and enabling factors. Transportation Research Part A: Policy and Practice 131, 283–295. doi:10.1016/j.tra.2019.09.028.

Liang, X., Correia, G.H.d.A., van Arem, B., 2016. Optimizing the service area and trip selection of an electric automated taxi system used for the last mile of train trips. Transportation Research Part E: Logistics and Transportation Review 93, 115–129. doi:10.1016/j.tre.2016.05.006.

MAAS-Alliance, 2019. What is maas? URL: https://maas-alliance.eu/homepage/what-is-maas/.

Markham.ca, 2018. About markham. URL: https://www.markham.ca/wps/portal/home.

Meshkani, S., Farooq, B., 2021. Graph-based many-to-one dynamic ride-matching for shared mobility services in congested networks. arXiv:2101.08657.

Ministry of Labour, Training and Skills Development, 2021. Minimum wage. URL: https://www.ontario.ca/document/your-guide-employment-standards-act-0/minimum-wage.

MVG, 2018. Mvg isartiger. URL: https://www.mvg.de/services/mobile-services/mvg-isartiger.html.

Pentikainen, P., 2016. Demand-Responsive Transit in Innisfil. Technical Report DSR-143-15. Innisfil.

RideCo, 2018. Solving the first mile-lastmile on-demand. Technical Report. RideCo.

Ronald, N., Thompson, R., Winter, S., 2017. Simulating ad-hoc demand-responsive transportation: a comparison of three approaches. Transportation Planning and Technology 40, 340–358. doi:10.1080/03081060.2017.1283159.

Ruch, C., Horl, S., Frazzoli, E., 2018. AMoDeus, a simulation-based testbed for autonomous mobility-on-demand systems, in: 2018 21st International Conference on Intelligent Transportation Systems (ITSC), IEEE. pp. 3639–3644. doi:10.1109/itsc.2018.8569961.

Salazar, M., Lanzetti, N., Rossi, F., Schiffer, M., Pavone, M., 2020. Intermodal autonomous mobility-on-demand. IEEE Transactions on Intelligent Transportation Systems 21, 3946–3960. doi:10.1109/TITS.2019.2950720.

Sanaullah, I., Alsaleh, N., Djavadian, S., Farooq, B., 2021. Spatio-temporal analysis of on-demand transit: A case study of belleville, canada. Transportation Research Part A: Policy and Practice 145, 284–301.

Shen, Y., Zhang, H., Zhao, J., 2018. Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in singapore. Transportation Research Part A: Policy and Practice 113, 125–136. doi:10.1016/j.tra.2018.04.004.

Sieber, L., Ruch, C., Hörl, S., Axhausen, K., Frazzoli, E., 2020. Improved public transportation in rural areas with self-driving cars: A study on the operation of swiss train lines. Transportation Research Part A: Policy and Practice 134, 35–51. doi:10.1016/j.tra.2020.01.020.

Statista, 2018. Rideshare vehicle of choice among uber and lyft drivers in the united states as of february 2018. URL: https://www.statista.com/statistics/830053/rideshare-vehicle-of-choice-among-uber-and-lyft-drivers-us/.

Statistics Canada, 2016a. Focus on geography series, 2011 census. URL: https://bit.ly/2DpHqeL.

Statistics Canada, 2016b. Main mode of commuting, 2016 census. URL: https://bit.ly/2OuT0vy.

Statistics Canada, 2018. Average usual hours and wages by selected characteristics, monthly, unadjusted for seasonality, last 5 months. URL: https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410032001, doi:10.25318/1410032001-ENG.

Teodorović, D., Orco, M.D., 2008. Mitigating traffic congestion: Solving the ride-matching problem by bee colony optimization. Transportation Planning and Technology 31, 135–152. doi:10.1080/03081060801948027.

Toronto City Planning, 2016. Toronto Employment Survey 2016. Technical Report. City Planning Division Strategic Initiatives, Policy & Analysis Research and Information.

TTS, 2016. Transportation tomorrow survey 2016. URL: http://www.transportationtomorrow.on.ca/.

Vijayakumar, N., El-Geneidy, A.M., Patterson, Z., 2011. Driving to suburban rail stations. Transportation Research Record: Journal of the Transportation Research Board 2219, 97–103. doi:10.3141/2219-12.

Wallar, A., Schwarting, W., Alonso-Mora, J., Rus, D., 2019. Optimizing multi-class fleet compositions for shared mobility-as-a-service, in: 2019 IEEE Intelligent Transportation Systems Conference (ITSC), IEEE. pp. 2998–3005. doi:10.1109/itsc.2019.8916904.

Wang, C.N., Dang, T.T., Le, T.Q., Kewcharoenwong, P., 2020. Transportation optimization models for intermodal networks with fuzzy node capacity, detour factor, and vehicle utilization constraints. Mathematics 8, 2109. doi:10.3390/math8122109.

Wang, F., Ross, C.L., Karner, A., 2019. Understanding the influence of mobility as a service (maas) on job accessibility and transportation equity, in: Transportation Research Board 98th Annual Meeting, p. 22.