EXPLORING FIRST-MILE SOLUTIONS FOR NORTH AMERICAN SUB-URBIA: A CASE STUDY OF MARKHAM, CANADA

Johanna Bürstlein, B.Eng., Graduate Student, Corresponding Author
Department of Civil Engineering, Karlsruhe University of Applied Sciences
Moltkestraße 30, Karlsruhe, 76133, Germany
And
Department of Civil Engineering, Ryerson University
350 Victoria Street, Toronto, ON M5B 2K3, Canada
Email: johanna.buerstlein@gmail.com

Dr. Bilal Farooq, B.Sc, MA.Sc, Ph.D
Canada Research Chair in Disruptive Transportation Technologies and Services
Department of Civil Engineering, Ryerson University
350 Victoria Street, Toronto, ON M5B 2K3, Canada
Email: bilal.farooq@ryerson.ca

Word count: 11,950 words text + 3 table(s) × 250 words (each) = 12,700 words

Submission Date: July 8, 2019

ABSTRACT
We explore Mobility as a Service (MaaS) solutions for the first mile commuting in Markham, a Toronto suburb. The focus is on connecting commuters to the regional train service, called GO train. The aim of this study is to develop a detailed scenario analysis using different types of MaaS solutions that can complement existing public transport. Various use cases of demand responsive vehicles are explored in terms of individual capacity and fleet-size. It is assumed that the existing car-based trips to the train stations would be replaced by such demand responsive vehicles. Two scenarios which involve Quasi-MaaS and extensive MaaS are developed and compared. We used wait-time, travel time, demand served, and cost as the indicators to evaluate various options. Additionally, cases of Quasi-MaaS and extensive MaaS are created. Our study considers ride-sharing with rider capacity of up to 7 simultaneous passengers per vehicle. The software applies to different fleet sizes and vehicle types (4-seated and 7-seated vehicles) and coordinates 1865 trip requests within the morning peak from 7 am to 10 am.

TABLE OF CONTENTS

Abstract II
Table of Contents III
List of Tables IV
List of Equations V
List of Figures VI
1 Introduction 1
2 Literature Review 3
2.1 Problems of Public Transit in low-density Area 3
2.2 “Mobility as a Service” and Examples of “On-demand Services” 3
2.3 Traffic Assignments 5
3 Case Study and Descriptive Analysis 9
3.1 Research Area - Markham 9
3.2 GO Transit and its Demand 12
4 Methodology 16
4.1 Base Case - *Status Quo* 16
4.2 Approach A - Quasi MaaS 17
4.3 Approach B - MaaS 18
5 Results 21
5.1 Approach A - Quasi MaaS 21
5.2 Approach B - MaaS 22
5.3 Comparative Results 29
6 Conclusion and Future Work 31
References VII

LIST OF TABLES

Table 1 Headway in minutes per time interval 18
Table 2 Cost analysis of Approach A and B..... 29
Table 3 Comparative analysis of the scenarios..... 30

LIST OF EQUATIONS

Equation 1 Route Choice in Stochastic Traffic Assignment (17)..... 6
Equation 2 Headway Calculation 17

LIST OF FIGURES

Figure 1 Structure of a Public Transportation Trip 1
Figure 2 Dependencies in Public Transport in low-Density Areas 3
Figure 3 Types of Traffic Assignments 6
Figure 4 Iterative Framework of a Dynamic Traffic Assignment (23) 7
Figure 5 Location of Markham within the GTA 9
Figure 6 Compared Population Growth in Canada (25) 10
Figure 7 GO train stations located in Markham 11
Figure 8 Modal Split of all trips with origin or destination in Markham 11
Figure 9 Number of Cars per Household in Markham (27) 12
Figure 10 Traffic Modes for the first mile to Unionville and Markham GO Rail Station (27) 12
Figure 11 Traffic Modes for the first mile to Centennial and Mount Joy GO Rail Station (27) 13
Figure 12 Demand bars of car trips to GO Rail Stations (27) 14
Figure 13 Frequency strength divided by time and train station (27) 15
Figure 14 Traffic Volumes of the Base Case between 7 am and 10 am 16
Figure 15 Location of Screenlines within Markham 17
Figure 16 Pick-up/Drop Off Points (PUDO's) 19
Figure 17 Boxplot in vehicle time of Quasi MaaS 21
Figure 18 Demand Satisfaction Maas (detour factor 1.5) 22
Figure 19 Occupancy Rate of Maas (detour factor 1.5) 23
Figure 20 In Vehicle Time of MaaS (detour factor 1.5) 24
Figure 21 Origin Wait Time of MaaS (detour factor 1.5) 25
Figure 22 Demand Satisfaction MaaS (detour factor 5) 26
Figure 23 Occupancy Rate for MaaS (detour factor 5) 27
Figure 24 In Vehicle Time of MaaS (detour factor 5) 27
Figure 25 Origin Wait time of MaaS (detour factor 5) 28

1 INTRODUCTION

Mobility is a basic necessity, which is constantly changing both in terms of space and time. Most of the time, people all around the world prefer to use private cars to travel to work instead of public transport. Most of the commuter trips are single occupant vehicle trips. In North America, for example, trips by car as a driver represent approximately three-quarters of all commuter trips (1). Local governments recommend the use of public transport in order to reduce the negative impacts of car trips such as pollution, traffic jams and overcrowded parking lots. Due to the low population density in many suburban and rural areas, high-frequency public transport may not be economically viable and thus leads to longer commuting times. The utilization of public transport is often low, e.g., roughly 12% in Canada (1, 2). 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 these trips is mostly covered by bus or rail services but passengers need to complete the first or last portion of the trip using other modes like walking, cycling, driving or public transport (see Figure 1).
To accommodate first and last mile of home-based trips, to and from transit stations, transportation agencies must find adequate and sustainable solutions. An option can be to replace driving trips with multioccupancy ridesharing trips (see Figure 1) and the establishment of demand-responsive systems.

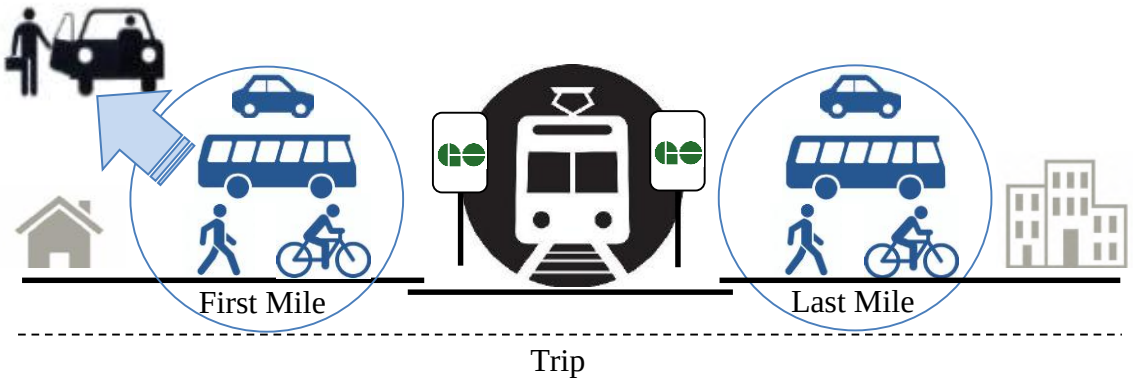


Figure 1 Structure of a Public Transportation Trip

Those systems run without fixed routes nor timetable and include sharing the ride with other passengers. Routes are demand-responsive and trip requests are transmitted from the passenger to the operator. This type of mobility is often titled Mobility as a Service (MaaS). Uberpool and Lyft-line are seen as the two best-known operators who provide such a service.
The above-mentioned characteristics regarding North American suburbs apply to the City of Markham, which is a Suburb of Toronto, Canada. Local transit is barely used within the suburbs but at the same time, the regional commuter train to Toronto, as the center of the Greater Toronto & Hamilton Area (GTHA), is highly demanded. This study focuses on the effect of the implementation of an on-demand rideshare service. Especially experienced wait times and changes in travel times compared to travel times when using a private vehicle are examined. Additionally, it is tested how those results are varying when changing parameters like fleet size, detour factor and vehicle capacity. The current public transport is not considered in the simulation and is replaced by the ridesharing service.

Operating with an on-demand service for the first mile in this area could change the commuters experience in a positive way. Problems like congestion, lack of parking lots at the GO train stations and pollution can be tackled because single occupancy trips will convert to multiple occupancy trips. Accordingly, link volumes can be reduced and parking lot demand

could be diminished. This study states one of the first approaches of operating with on-demand rideshare service as part of a trip chain in a North American suburb. Additionally, the focus lies not on the computer science like in many other studies but on finding travel and wait times as realistic as possible. The case study called “Solving the first mile- last mile on-demand” from RideCo, includes a similar approach which is developed and was operated in a suburb called Milton in the GTHA. The operating area is smaller than Markham and contains only one GO train station (3).

In Chapter two, a closer description of the public transport commuting problem in low density areas and examples of on-demand transportation are given. As well, a comparison of traffic assignments is made due to the fact that the simulation is based on the stochastic dynamic traffic assignment. After, an overview of the research area and the corresponding demand of Markham are presented in Chapter three. Accordingly, we describe the methodology which is used to create the scenario cases in Chapter four. In Chapter five, we present the results and in Chapter six the conclusion, a summary of the thesis and outlook on future work.

2 LITERATURE REVIEW

This chapter gives an overview of the situation regarding public transport in low-density areas and some examples where ridesharing as a part of public transport is already implemented. Furthermore, different traffic assignments are explained because it is a basic element of the simulation software.

2.1 Problems of Public Transit in low-density Area

Regions with low population and widely spread development are called low-density areas. A metropolitan city like Toronto with a population density of 4149.5 persons per square kilometer is considered as a high-density area, whereas its suburbs, for example, Markham with a density of 1419.3 persons per square kilometer is categorized as a low-density area (4, 5). These areas often struggle with developing public transport which works cost-efficient and serves the needs of the residents.

Public transport services can be considered sustainable mobility solutions when compared with private vehicles. Highly efficient in terms of energy and space and with great capacity, public transport can be a good alternative to using private vehicles. This can be seen in many high-density areas, but only in a few low-density regions. Due to long distances within the suburban areas, public transport lines have to serve a huge area. As a consequence, the lines are long and have a high cycle time. In order to keep the cycle time within reasonable limits, stops are widely spread and the access time can be high, which decreases the passengers' comfort. Many vehicles are needed to serve the lines adequately which is resulting in high operation cost. As an outcome of high access times, widely spread stops and poor coverage of the area, potential passengers prefer to use their private vehicles. The demand for public transport, which is already little due to the low population density, is thereby further reduced. Low demand means fewer passengers and this is less cost effective for the public transport operator. To ensure cost efficiency, fewer vehicles are used, the headway between vehicle journeys increases, lines are shortened or shut down. Decreasing passenger numbers can be seen as an effect. This vicious cycle is displayed in Figure 2.

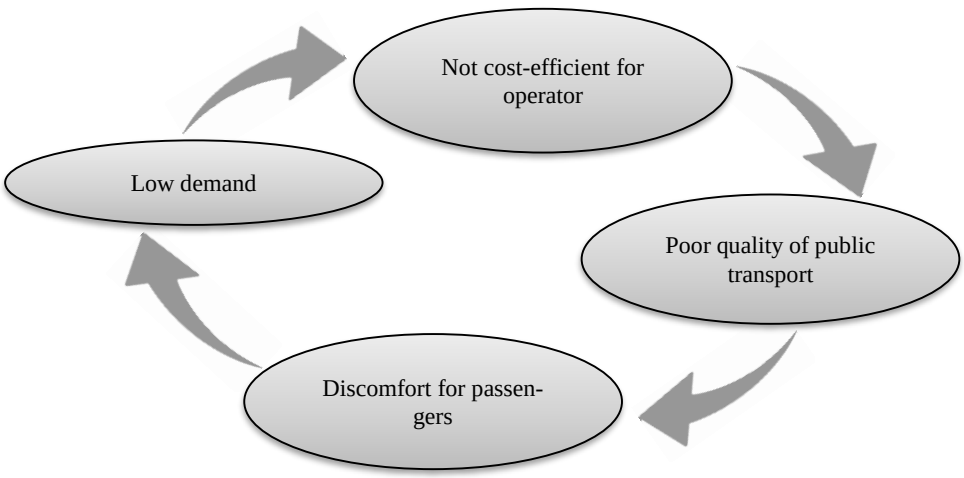


Figure 2 Dependencies in Public Transport in low-Density Areas

2.2 "Mobility as a Service" and Examples of "On-demand Services"

The traffic sector is in a period of significant change with new technologies, products and services which can change the expectations and possibilities of everyone when it comes to mobility. Especially the market for intelligent mobility develops quickly. Users, operators, companies and administration departments (e.g. of cities or municipalities) can see the potential of mobility opportunities as a part of a big, integrated system (6). MaaS is a system which

combines various forms of transport services into a single mobility service (7). It was born in Finland where it is already established in the national transport policy (8). Various projects all over the world are planned or starting up (7). Many of them contain ridesharing, which is a fundamental content in this thesis. Therefore, on-demand service and rideshare examples are described and underpinned by examples.

Ridesharing describes the arrangement in which a passenger is traveling in a vehicle which is driven by its owner or a driver for a fee (9) and began at the time before the majority was using advanced telecommunication technology like smartphones. In the private sector e.g. sharing the ride to work with your neighbor who works at the same company. With the development of technology and the aspiration for greater flexibility, new models were established which can also work demand-responsively. A selection of those will be discussed in the following paragraphs.

"GO Connect" - First- and last-mile solutions in Milton
In one of Toronto's suburbs called Milton, the public transit agency Metrolinx has implemented a new way for offering first- and last mile solutions to train station together with RideCo, a company that builds on-demand transit systems. This project was implemented to improve access to the local GO Transit station and to reduce reliance on an overcrowded parking lot. The goal of this attempt was to encourage switching away from driving oneself by car towards using shared mobility and to improve operating efficiency. As a result, one quarter of riders switched away from solo car rides to using the ridesharing service. Additionally, the net cost per ride was 27 percent less when compared to the price of the municipal bus. The dynamic route on-demand service was launched as a one-year pilot project and started in March 2015. A ride can be booked using a mobile app or website on–demand or days in advance. Than a specific pickup and drop-off time up on booking a ride are given. The routing of vehicles is dynamically based on passenger's locations. Additionally, riders share their rides with others going in the same direction. By constraining the sharing and journey times it is ensured that all riders arrive at their destination by the promised drop-off time (3,10).

On-demand bus in Belleville
Belleville is a Canadian city with a population of 50.700 people (11). An on-demand late-night bus is running as a one-year pilot project during low-demand hours. It is used to reduce operating costs and to enhance convenience which should increase the ridership. To define a pickup and drop off point as well as the pickup time, a request is made by placing a call or using a web application. The bus line usually covers a route of 22 km and a duration of 55 min (12,13).

Ride-hailing service as a primary form of public transit in Innisfil
Innisfil with a population of 36.500 inhabitants established a demand-responsive transit service (14,15). A requested vehicle is sent to pick up riders as they are requested. It is more cost-efficient for the town to cooperate with Uber and local taxi companies compared to a fixed route service with buses. The price difference between the ride service price and the fare paid from the passenger is subsidized from Innisfil. With this partnership, the cost of 3 to 5 Canadian Dollars for using the ridesharing service is similar to what passengers would otherwise pay for traditional bus transit (15).

Demand responsive feeder system in Millbrae
A basic demand responsive feeder system for the city of Millbrae, California is presented by Cayford and Yim (16). During low-demand periods and based on actual demand, buses can deviate from their fixed routes as well as from their scheduled departure times. The route deviation is limited to skip portions of the fixed route when there is no demand for drop-offs. Buses operate according to the fixed schedule during high-demand periods. Demand responsive transit (DRT) is a system that collects transit riders from neighborhoods and takes them to transit stations. One of the common integration options between a fixed-schedule system and an on-demand system is the Demand Responsive Connector (DRC). Such systems typically operate within a service area and move passengers to and from transfer points that connects to a major fixed-route transit network (16).

Demand responsive mobility service in Munich
As a supplement to public transport like subway, tram, bus, bike- and car sharing, the MVG (Müncher Verkehrsgesellschaft) IsarTiger presents a new component in Munich's' ridesharing offer. It's a mobility service which can be requested according to personal needs using a smartphone to reserve a seat in a vehicle (van size). The application calculates the route according to the chosen destination within the operating area. Accordingly, the system checks the available vehicles and computes a route in consideration of further requests. As the service is meant to share rides, other passengers can be picked up or dropped off along the route with short detours. Especially private vehicle owners should be attracted to switch to public transport, as it is almost as convenient and comfortable as private transport and environmentally friendly. The service is not running yet for public use, but the necessary coordination with the authorities are currently taking place. A first test phase was operated in 2018 and a second one is following in April 2019. If the second phase with a duration of approximately one-year is successful and the operation is cost-efficient, the city wants to continue with the service and involve local taxi companies as well. The operating area is located west of the center with a size of approximately 30 km^2. This region will be served with a fleet size of 20 vehicles, containing gas-powered vehicles with a capacity of 6 passengers and also electric vehicles which can transport up to 3 riders (17).

2.3 Traffic Assignments

The process of allocating origin-destination pairs to the existing suitable road network is called traffic assignment (18). It is based on specific traveler route choice criteria which are the travel impedance of the transportation network. With traffic assignments it is possible to determine information about which routes are used in between the traffic zones and how much traffic is going to be expected. To obtain this information, the number of trips between the zones as well as available routes have to be implemented.

Traffic assignments can be distinguished in two main categories, the stochastic assignment and the deterministic assignment. Furthermore, they represent the fourth step of the four-step travel demand model (18). A summary of the different combinations is shown in Figure 3. In our case the stochastic dynamic assignment is used for the simulation.

Additionally, traffic assignments can have static or dynamic characteristics. Static means that all the demand is loaded at the same time and the travel time on link level is independent of the time of day. Whereas dynamic means that demand is gradually loaded in the network and travel times are time dependent.

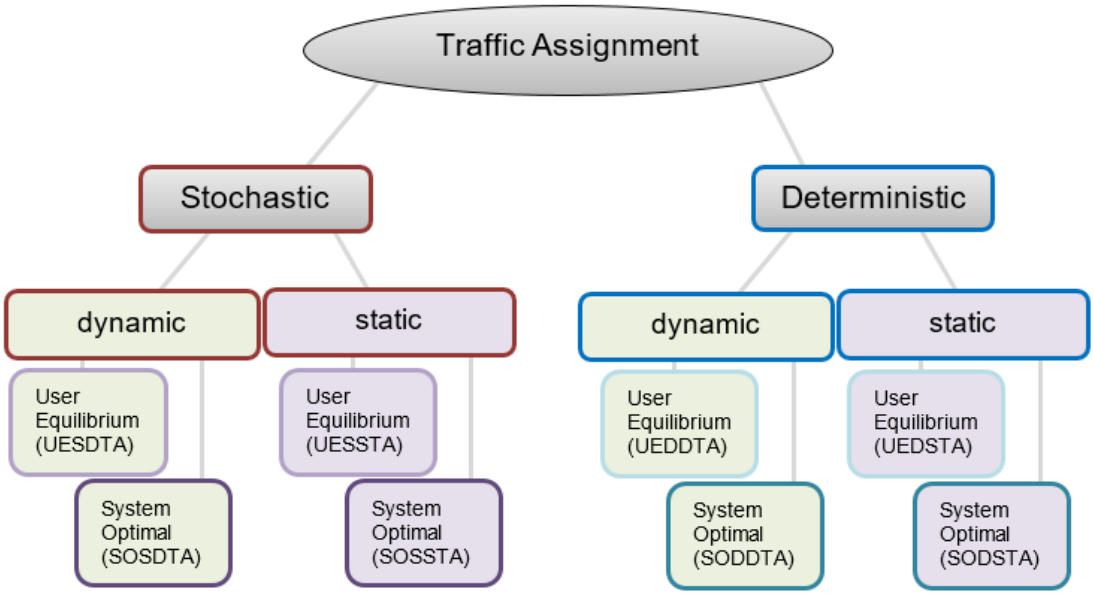
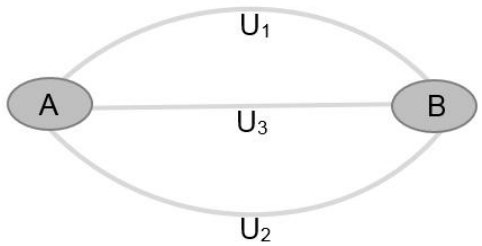


Figure 3 Types of Traffic Assignments

Deterministic vs. Stochastic Traffic Assignments
Traffic assignment models are mostly classified based on two criteria. On the one hand the congestion effects in travel times and on the other hand errors in the user's perception of actual travel times. Deterministic models are not subjected to randomness and therefore are based on the assumptions that arrival and departure times are deterministic variables and hence, the same outcome is produced for each application. The flows are satisfied as the first Wardrop's principle (19).

The model is stochastic when the outcomes change and the truth of outcomes is not known with certainty. Randomness is very important and a unique characteristic of stochastic models. During the assignment, random variables are used and are producing different model results. As a conclusion, the results of a simulation, based on a stochastic model, cannot be predicted with certainty before the analysis begins (20). Furthermore, stochastic assignment models take into account errors in user's time perception by representing link travel times as random variables. These are distributed across the population of trip makers. For example, a trip from A to B with n possible paths and different utility values U_i, like travel times. A method to find out the probability P of using route i is shown in Equation 1.



$$P(i) = \frac{e^{Ui}}{\sum_{i=1}^{n} e^{Ui}}$$

Equation 1 Route Choice in Stochastic Traffic Assignment (21)

The Stochastic Traffic Assignment shown in Equation 1 is very realistic, but the competing path identification is difficult. Additionally, the complexity of utility functions is very high and the computational complication is horrendous. Nevertheless, it is the most widespread stochastic assignment and is based on exponential (logit) trip diversion formula (21).

Static vs. Dynamic Traffic Assignments

The route choice is based on the travel time needed to complete a trip between an origin-destination pair. For example, assume that route A and B are available between two zones. If the travel times of A and B are equal or their ratio is one, 50% of the travelers would use route A and 50% would use route B. As the travel time on route A gets relatively large compared to route B, most travelers would tend to shift towards route B and vice versa. That means that traffic assignment and route choice behavior represent a classic equilibrium problem. The route choice decision can be seen as a function of travel times. The higher the travel time, the less desirable it becomes for the traveler. Travel times are determined by traffic flow, which is a product of route choice decisions. No matter how simple the behavior model is, mutual dependencies and circular relationships are maintained. To investigate these phenomena, some concepts from game and economics theory can be applied. Also the capacity restraint method is involved in the process. Capacity restraint assignment tries to approximate an equilibrium solution by iterating between all-or nothing traffic loadings and recalculates link travel times based on a congestion function that reflects link capacity (18). The most fundamental method of capacity restraint is the Bureau of Public Roads (BPR) Function. As the travel times increase significantly, large levels of congestions can be observed. This point of increase is also the point where the route choice is influenced. The route choice behavior is often modeled based upon Wardrop's Principles (22).

The first Wardrop principle states that users choose the route that minimizes their own travel time and is called user equilibrium. If every user minimizes their travel time, most travel times will be equal to one another. That means that travelers can not improve their travel times by unilaterally changing routes. This principle is called User Equilibrium and can be either static or dynamic (22).

The second Wardrop principle states that users distribute themselves on the network in such a way that the average travel time for all users is minimized. If they are minimizing the average travel time, the total system travel time minimizes as well. The difference to the first principle is, that some users are experiencing a higher travel time and others a shorter travel time. Nevertheless, in total, the average travel time decreases and the whole system is optimized. This principle is called System Optimal and can be either static or dynamic (22). The process of getting to User Equilibrium or System Optimal works with an iterative framework which is shown in Figure 4. First, the travel time is calculated and the shortest paths for the route is found. Then the route choice is adjusted towards the equilibrium. This leads again to the calculation of the route travel time.

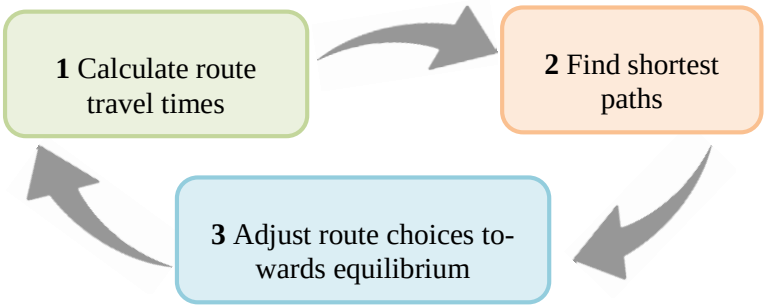


Figure 4 Iterative Framework of a Dynamic Traffic Assignment (23)

This iterative framework is also known as the network loading problem. Known values are the paths and departure times for each traveler. By integrating them onto the network, the experienced travel times can be calculated.

Dynamic Stochastic Traffic Assignment

The dynamic stochastic assignment is a combination of the above described dynamic and stochastic assignment and differs from all other assignment procedures as a result of the explicit modeling of the time required to complete trips in the network.

Depending on the time-dependent capacity, not only are different routes chosen at different times but if necessary the actual departure time is shifted with respect to the desired departure time. This is the assignment which is used for the simulation of this project and is operationalized from the software.

3 CASE STUDY AND DESCRIPTIVE ANALYSIS

This chapter contains information about the research area in terms of geographical location, current population, public transport options and mode choices. Additionally, we present a trip analysis which shows Markham's modal split and demand towards the GO train stations.

3.1 Research Area - Markham

Markham, a suburb of Toronto, is part of the Greater Toronto Area (GTA) and is located in Ontario, Canada (see Figure 5). Over 355,000 residents call Markham their home - the largest of nine communities in York Region of the GTA. Additionally, the city is home to more than 1,500 high tech and life science companies and more than 210 foreign firms (24).
In the past few years Markham has gone through a phase of strong development. The population has been growing and the site development of the area is continuing.

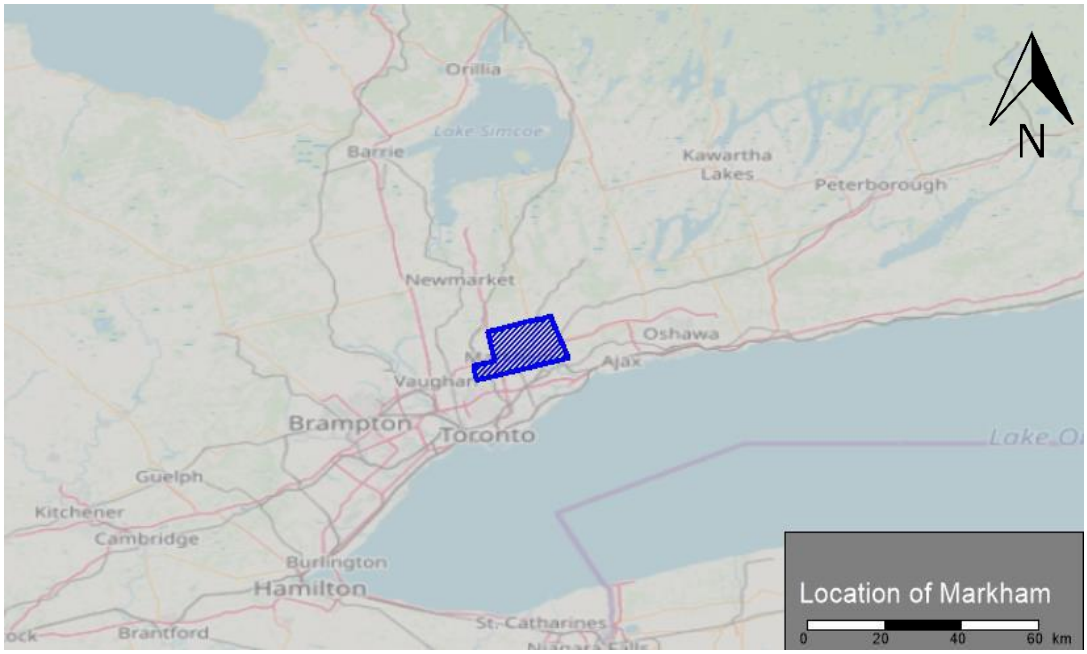


Figure 5 Location of Markham within the GTA

Figure 6 shows the estimated population growth from 2018 till 2023 comparing Markham to Toronto and Canada. Markham is with 8.4% growth in population the strongest rising area. The total population of Canada will grow by about 4.8% and the City of Toronto about 4.1% (25).

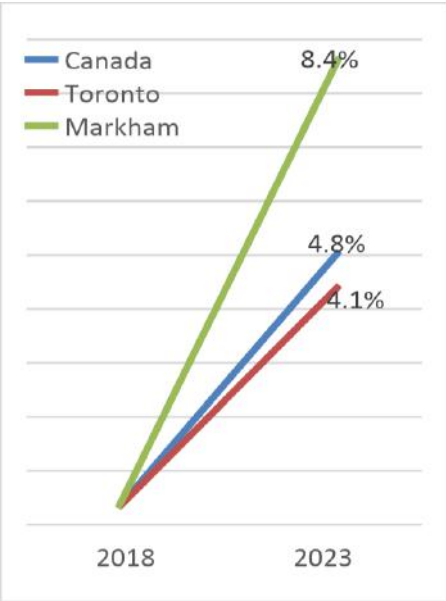


Figure 6 Compared Population Growth in Canada (25)

With a higher population, the demand for transportation is also going to increase which is leading to the conclusion that congestions and traffic jams will also grow if the traffic infrastructure is not changing. Congestion is already a major issue being faced in downtown Toronto, where many residents of Markham commute to and from for work. Due to this, many choose the regional public transport, GO Transit, to reach the center of the GTA.
GO Transit is a regional public transport operator of the GTA and provides service to downtown Toronto. It has four train stations in Markham which are marked with 'H' in Figure 7. Unionville station is closest to Union Station (downtown main GO station) and a trip by GO train 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, the train needs 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 (26).

In the presented thesis we use the Transportation Tomorrow Survey (TTS) which collects household and transportation information of the GTA every 5 years since 1986. For this study, the data from 2011 is used. Household and trip data is projected to the year 2018 with the growth factor of 18% which represents the population growth from 2011 to 2018 (25, 27). Statements about the first mile and its traffic mode can be made, by analyzing another data set of the TTS. Figure 8 shows that more than two third of all trips with destination, origin or within Markham are covered per car. The second most common transport mode is traveling as a co-driver. Together they represent almost 90% (71%+16.7%) of all trips. Public transport use, joint with use of GO Transit, is represented with a share of barely 8% (6.2%+1.5%). Walking and cycling are modes that are hardly considered with 2.8% for walking and 0.29% for cycling. 1% of all passengers use buses, 0.12% prefer taxi service and 0.03% go by motorcycle. The rest of the trip makers use other transport modes (27).

Figure 7 GO train stations located in Markham

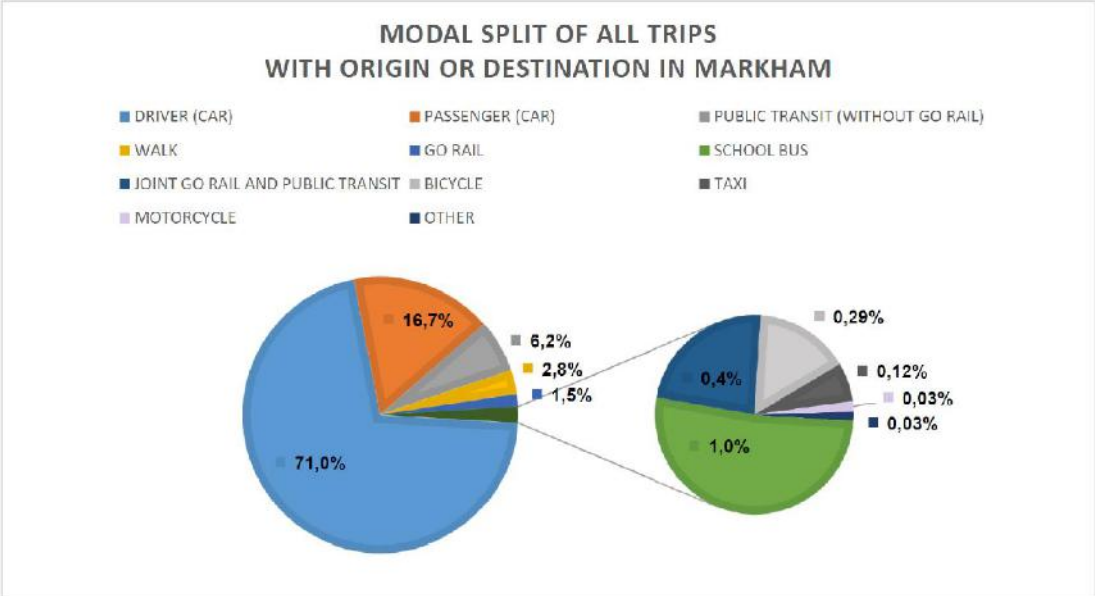


Figure 8 Modal Split of all trips with origin or destination in Markham

Summing up the analysis of the modal split, it can be said that Markham has a high preference to use motorized private vehicles. A closer look at the TTS provides information about the number of cars per household.

Figure 9 makes clearly visible that the number of households having no car is infinitesimally small. Households without a car are shown in bright red and those bars appear next to the ones of households with one or two cars almost invisible. Nearly all households in Markham own at least one car and the majority of the household can afford to have two cars. Households with three or more cars are represented with a lower number. This can result due

to a smaller amount of households with five or more persons. Most households are families, so a household represented with a higher number of persons is very likely to have children living there. They are involved in the survey but are not potential drivers. Nonetheless, the TTS gives a good overview of private vehicle use. As a conclusion, it can be said that people living in Markham are very likely to have access to a car. This can be as sign that they are highly dependent on cars and accordingly are using them a lot.

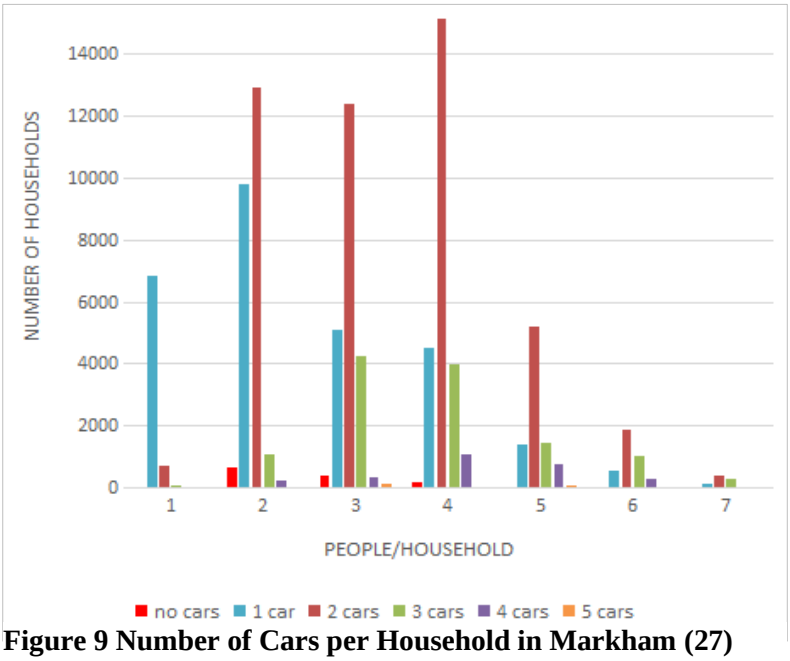


Figure 9 Number of Cars per Household in Markham (27)

3.2 GO Transit and its Demand

Passengers are using the service of GO Transit daily. The TTS provides data about which stations are frequented and about which traffic mode is used for the first mile. These statements are displayed in the following Figures 10 and 11 relating to each examined station.

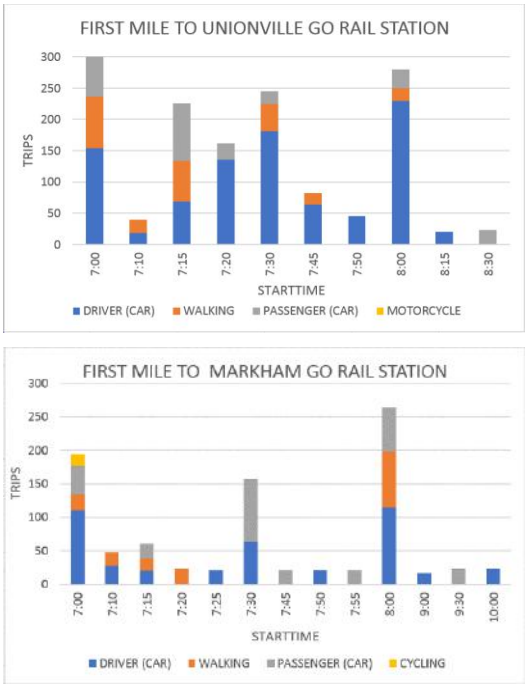


Figure 10 Traffic Modes for the first mile to Unionville and Markham GO Rail Station (27)

Figure 10 presents the modal split of first mile trips to Unionville and Markham GO Rail Station defined by time periods. The times are the starting times of each trip and are rounded to 5-minute intervals. Clearly, the colors blue and grey are dominating both diagrams, which means that a high percentage of trips are made by car. Blue means that the passenger is a car driver and grey signalizes that the trip is made as a car passenger. This leads to the insight the most trips are single occupancy trips. The second highest amount of trips are multiple occupancy journeys. A very small amount of passengers is walking to the train station or using a bicycle or motorcycle. Clearly visible is 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. Markham train station compared to Unionville station is less frequented by approximately one-third of the trips.

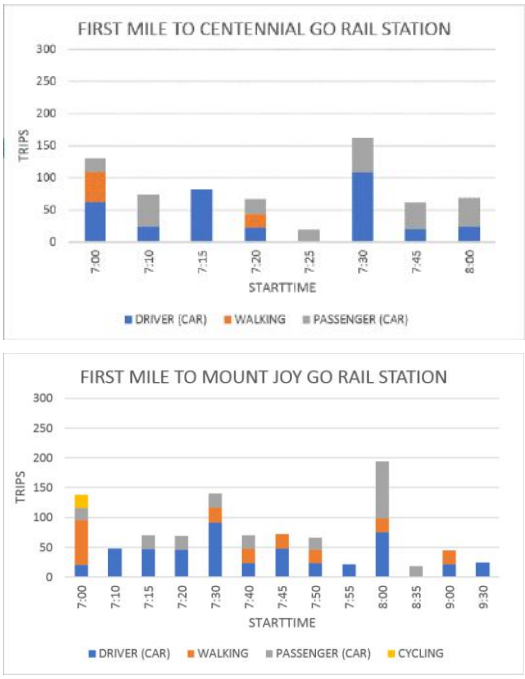


Figure 11 Traffic Modes for the first mile to Centennial and Mount Joy GO Rail Station (27)

Figure 11 states first mile trips to Centennial and Mount Joy GO Rail Station.
Like Figure 10, grey and blue are the preponderant colors of the bars. The majority of trips are made by using private motorized vehicles and the share of co-drivers is about one-third of all car trips. Centennial station is less frequented than Mount Joy station and the majority of trips are starting between 7am and 7:30am. Mount Joy station receives most passengers between 7:00am and 8am.

Taking into account primary mode and trip origin and destination, the first mile trips via car to GO train stations are extracted and used as the demand for the simulations. The demand for those OD-pairs is shown in Figure 12.

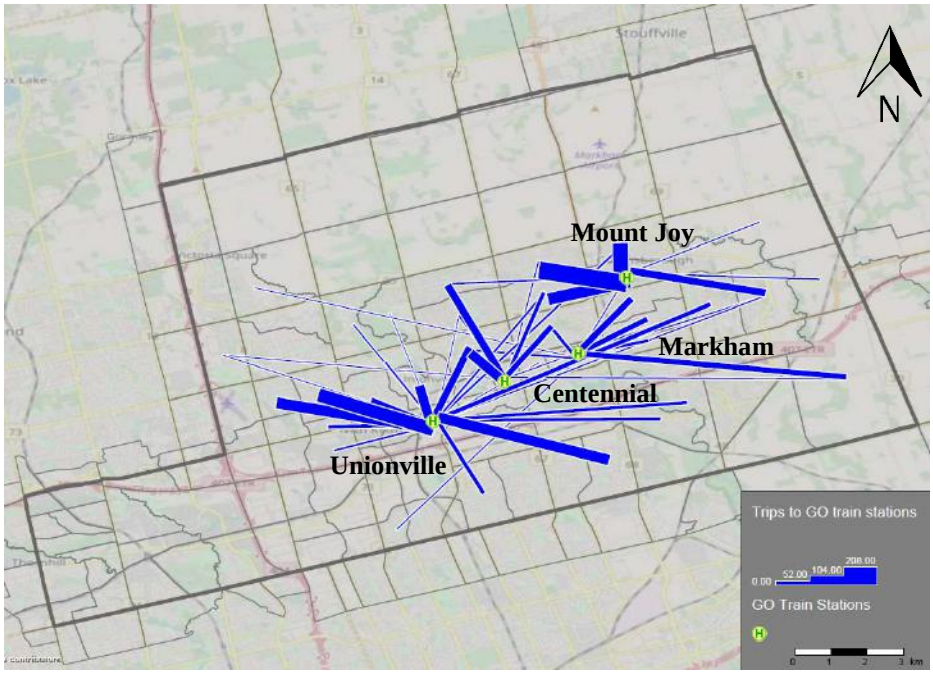


Figure 12 Demand bars of car trips to GO Rail Stations (27)

The bars mark the origin and destination of trips made by car, whereby the destinations are always a GO train station. Those are only the trips originating in Markham because the operating area of the rideshare service will only operate within Markham's borders. The thickness of the bars gives insight about the number of trips of each OD-pair. Another finding is the distance between the origin and destination of the trips. Due to the wide area of Markham, some passengers have to cover a big distance to the train station. To understand the demand bars better, Figure 13 gives more detailed information about the number of trips made by car and peak hour.

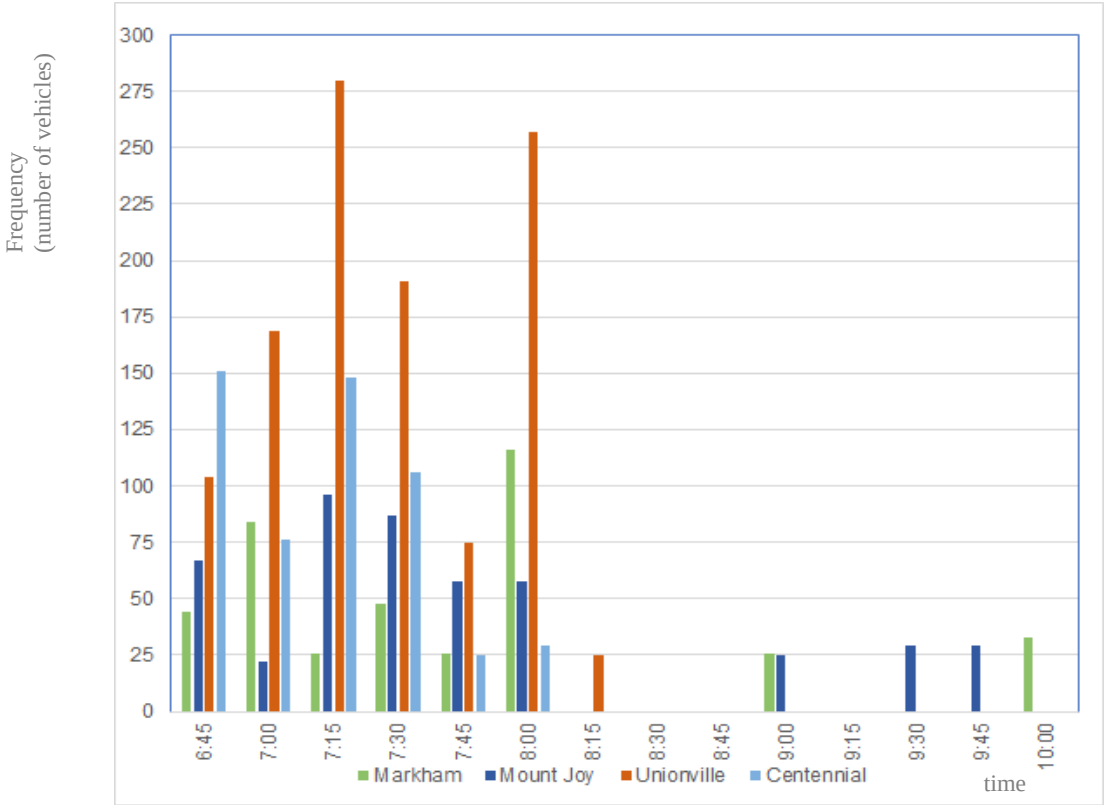


Figure 13 Frequency strength divided by time and train station (27)

Similar to Figure 10 and Figure 11, the most frequented stations are Unionville and Mount Joy, followed by Centennial and Markham. Most trips take place during the period from 7am to 8am. After, only a few trips are happening which can be the result of working hours. Unionville is very high frequented because it is the closest station to downtown in Markham and close to the Highway which makes it easy to access.

4 METHODOLOGY

In this study, the software PTV Visum is used to model the traffic network of Markham. Visum has macroscopic features and is used to give a holistic overview of the *status quo* and to measure the effects of development planning. The macroscopic approaches focus on the complete traffic flow taking into account the general traffic density and vehicles distributions. Whereas microscopic models focus on the mobility of each individual vehicle. It is decided to do a macroscopic simulation because the detailed impact of single intersections and vehicles are not of importance for the study focus.

The available trip data is base for a traffic estimation which mirrors the *status quo* (base case). Accordingly, the data is combined with information from Open Street Maps (OSM) and imported to PTV Visum in order to create a network. OSM combines information about maximum speed, capacity, number of lanes and intersection control types. Due to the lack of information concerning the signal timing, the network is simplified and PTV Visum is considering every signalized intersection as two way stop control. Using the dynamic stochastic traffic assignment, the volume and impedance of each link are calculated. With the input of free flow speed v_0 and link capacity, PTV Visum calculates free flow time t_0, as well as current speed v_{cur} and time t_{cur}, for each link and path between each OD-Pair. The focus lies on the current travel time t_{cur} of trips with a destination at the GO train stations.

4.1 Base Case - *Status Quo*

The demand data used to represent the *status quo* consists of expanded and projected trip demand of the Transportation Tomorrow Survey of 2011. This is 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.

Figure 14 Traffic Volumes of the Base Case between 7 am and 10 am

Traffic volumes of the base case are shown in Figure 14. Those result out of a dynamic stochastic assignment between 7am and 10am. Most traffic is on the Highway which crosses Markham in an east-west direction and on the northeast connections.

Calibration
Traffic counts of the program Cordon Count Data Retrieval System (28) are used to calibrate the system. Figure 15 shows which screenlines are within the borders of Markham.

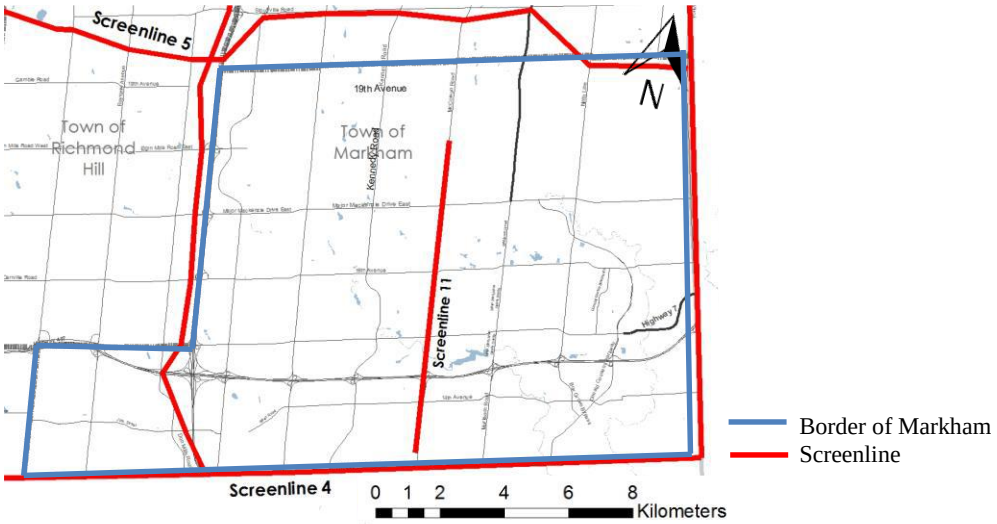


Figure 15 Location of Screenlines within Markham

As it is a very extensive study, there is only one screenline available for the research area. The total traffic volume from 6 am to 10 am 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.

4.2 Approach A - Quasi MaaS

The pickup service is modeled in PTV Visum as public transit which is operating with flexible schedules but fixed routes. Considering the first-mile demand, routes and timetables are changing in intervals of 15 minutes. We chose 15 minutes because within this time enough requests can be collected to plan the operating routes adequately. A ride is requested at least 15 minutes before the desired departure. Based on the requests, the timetable is calculated for a 15-minute interval and the service frequency depends on the vehicle seat capacity. Within this scenario, two cases are created, which operate initially with an infinite fleet size.
The main goal of this procedure is to satisfy the demand completely. For this reason, headways are calculated for intervals of 15 minutes. The fleet size is seen as infinite and an exact number of vehicles needed for optimal operation is computed later and is presented in Chapter 5. The ideal headway depends on the demand (number of trip requests), seat capacity, and time interval. Headways for different vehicles with varying seat capacities, such as van (7 seats) and car (4 seats) are calculated with Equation 2.

$$\mathbf{h}_{\text{OD-Pair}} = \frac{\textbf{(Seat capacity x duration time interval)}}{\textbf{Number of trip requests}}$$

Equation 2 Headway Calculation

Each OD-connection with a demand to one of the GO train stations is covered with a line route that runs with the above-calculated headway. The line route is serving 2 stops per OD-pair, one at the GO train station and one at the origin zone. Passengers are equally distributed to the stops within 15 minutes. Two different vehicle types are tested and the amount of

needed vehicles is calculated using the line blocking feature of PTV Visum. Concerning that the pick-up vehicles are using the speed data of the *status quo*, there is almost no difference in travel time. The main indicator will be the fleet size and service frequency.
To implement the approach in the current network, lines, belonging to each train station, are designed. A point to point approach is used, which means that a direct line route between the train station and pick up point is established. Only routes for zones with demand greater than zero are served. So, for every 15-minute interval, the amount of line routes changes according to the number of zones with a demand greater than zero. During the implementation, it became clear, that the results don't match the expected quality. For this reason, the approach is only executed for the GO train station 'Centennial'. We chose Centennial because it has average values in terms of demand and frequency compared to the other stations. Results can be replicated to other stations. Table 1 shows the headway in minutes per time interval.

Table 1 Headway in minutes per time interval

Headway [min]																
Vehicle Type/Seat Capacity			Car 4 seats							Van 7 seats						
	To Zone	From Zone	6:45	7:00	7:15	7:30	7:45	8:00	8:15	6:45	7:00	7:15	7:30	7:45	8:00	8:15
Centennial	2421	2376		2.4							4.2					
	2421	2410	2.5							4.4						
	2421	2417	2.8		1.2		2.4			4.8		2		4.2		
	2421	2418			2.4	2.4						4.2	4.2			
	2421	2419	1.7		1.7	1.2				3		3	2.1			
	2421	2433	1.9	2.8	2.8					3.2	4.8	4.8				
	2421	2434				2.1		2.1					3.7		3.7	
	2421	2435		2.1							3.7					
	2421	2452			2.1							3.7				
	2421	2454				2.1							3.7			

4.3 Approach B - MaaS

Another approach to examine travel and wait times can be an extensive version of MaaS. In contrast to conventional public transport, demand responsive transport generally does not require a timetable, a fixed sequence of stops or predefined stops. The pickup service is modeled with an Add On of PTV Visum called MaaS Modeler. This consist of two steps, the trip request generation and the tour planning and works therefore as demand responsive. Ridesharing (also called ride pooling) allows users to make individual trip requests. The trip requests include desired pick up time and location. The operator then weighs the trip request against the optimization of his operating costs. From users perspective, a trip request is made and the closest Pickup- / Drop-off Point (PUDO) to the requesters' location is assigned. Within a maximum wait time of 15 minutes, the passenger is picked up. The ride is ideally shared with other passengers and the total travel time of the passenger does not influence its contentment.
Optimizing transport performance without a timetable based on lines is a matter of tour planning. In addition to the dynamic supply, it is atypical for a macroscopic model that is not sufficient to model the demand down to zone and time-slice level. Modeling at node and time instants level is necessary to obtain a realistic model of the trip planning issue. A detailed map of all PUDO's can be seen in Figure 16.

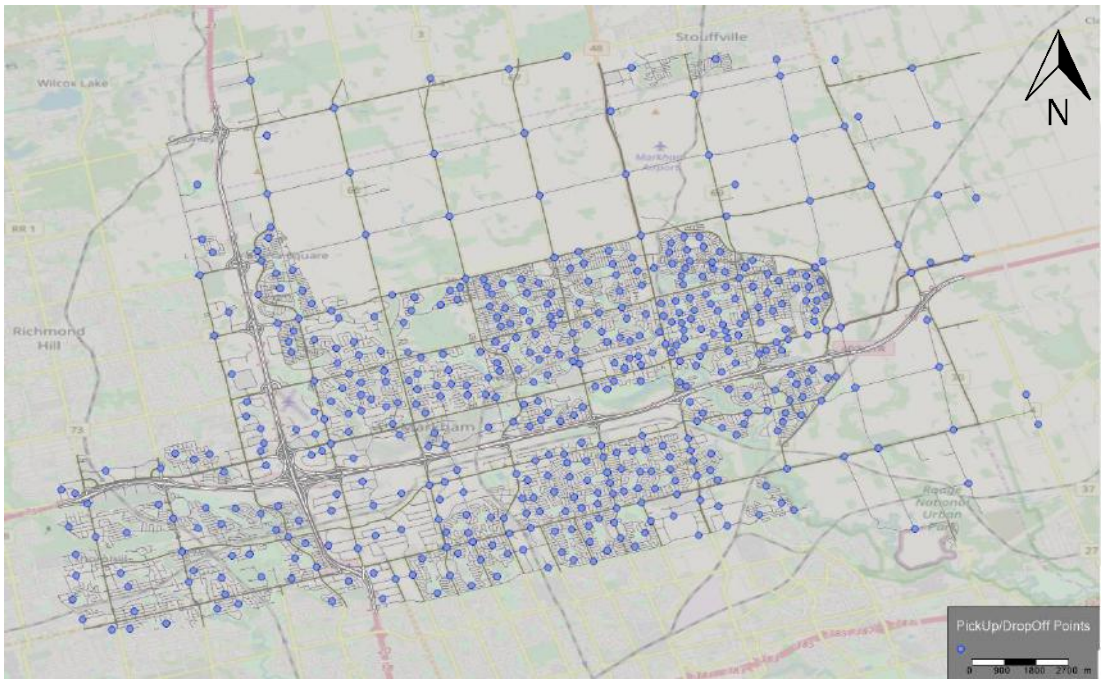


Figure 16 Pick-up/Drop Off Points (PUDO's)

Depending on the tested fleet size (optimal supply, 75% optimal supply, 50% optimal supply), served and unserved trip requests are calculated. In a first run the number of vehicles is set very high and the optimal supply, in number of vehicles, to obtain 100% served trips is calculated. Furthermore, the in vehicle time and wait time at the PUDO are calculated for each vehicle type (car, van) and fleet size. When running the procedure, several settings can be made, such as maximum occupancy of vehicles and number of passengers that request one trip. The distribution of the number of passengers traveling together per trip requests is 50% for one person requests and 50% for two person requests. The vehicles can pick up up to 4 passengers (car) or 7 passengers (van).

The tour planning procedure is based on skim matrices that have been calculated using the transport supply of conventional private transport (base case). Tours are optimized using trip distances and travel times. The procedure uses traffic zones as a basis but corrects the actual travel times and distances by comparing their spatial locations and zone centroids.
Not all trip requests are known prior to tour planning. This would lead to a too optimistic planning basis. Therefore, the tour planning issue is divided into time slices (15 minutes) that allow to model the dynamics of incoming trip requests. The tour planner only uses the trip requests known in the current time slice for scheduling vehicle utilization. The vehicle positions are adopted from the current or previous time slice. Optimization aims are meeting as many trip requests as possible, within the temporal and spatial restrictions defined, and using a minimum number of vehicles.

Using this procedure, the optimal number of vehicles to operate all trip requests is computed. As a start value a high number of available vehicles is used, which will be definitely enough to satisfy the demand. In this case we simulate an infinite fleet size with 1000 vehicles. The result of this procedure is called optimal supply and is further stated in Chapter 5. To examine changes in travel and wait times, the simulation is run with 75% and 50% of the optimal supply. The results for optimal supply, 75% of optimal supply and 50% of optimal supply are validated with 5 different seed numbers and simulation runs. Also the vehicle occupancy is examined and served and unserved trip requests are presented. Furthermore different detour

factors are tested. Connecting those results with travel and wait time, the insights are stated in Chapter 5.

5 RESULTS

This section presents the results gained from the procedures described in Section 4. First, we present the outcomes of approach A (see page 23) and compare them to the base case (see page 21). Approach A gives insights about in vehicle time, service frequency as well as fleet size. After, approach B (see Page 24) is analyzed in terms of in vehicle time, wait time and fleet size. The results are presented with regard to the different fleet sizes and vehicle types. Also varying detour factors are tested and differences are outlined. This is followed by a comparative analysis which is the base for the evaluation. The scenarios will be rated on a scale that reaches from minus three (very bad) till plus three (very good). A cost analysis is subsequently carried out in order to make the evaluation more meaningful.

5.1 Approach A - Quasi MaaS

The in vehicle time is shown in the boxplot in Figure 17. The results of the base case, which state the access to Centennial station by car or other modes and approach A, that represent trips using ridesharing for going to Centennial station.
The boxplots are divided into four equal groups called quartiles. Each of them represents 25% of all results and shows their margin. For the base case, quartile group one shows an in vehicle time between the minimum of 02:15 and 04:30 minutes.

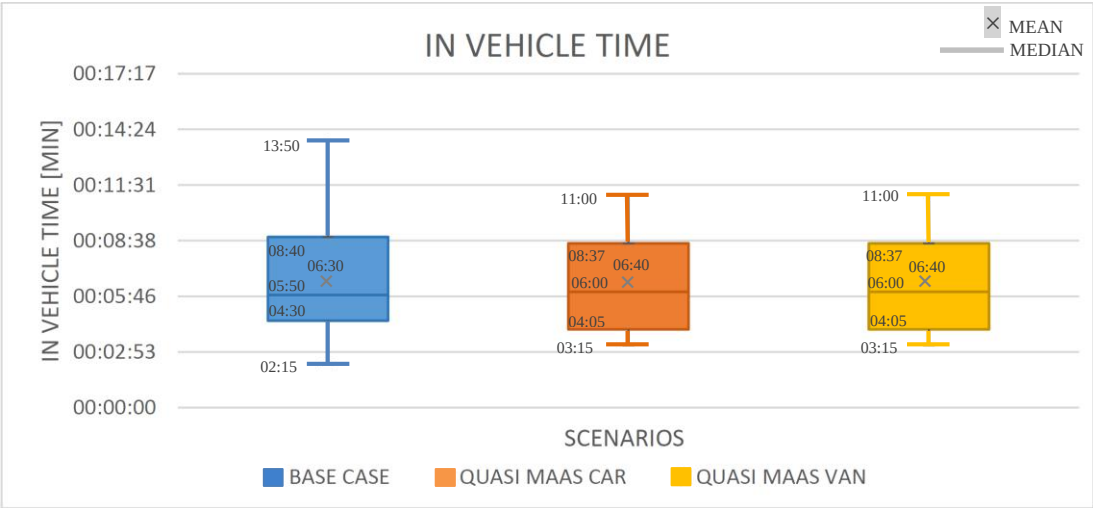


Figure 17 Boxplot in vehicle time of Quasi MaaS

The second quarter states the results between 04:30 and 05:50 minutes and the third quartile between 05:50 and 08:40 minutes. Quartile two and three are divided by the median with 05:50 minutes. The fourth quartile moves between 08:40 to the maximum of 13:50 minutes. It also stretches over the widest range and represents with quartile one scores outside the middle 50%. The mean value of the base case is 06:30 minutes.
The quasi MaaS pickup service for car and van has fixed travel times because the software works with timetables that are created before running the assignment. PTV Visum assigns the travel speed of cars (calculated in the base case) to the pick-up vehicles of Approach A. Accordingly, the in vehicle times of Approach A and base case are similar to each other, but differ slightly in the mean in vehicle time. The paths of the base case are starting and ending in the same OD-relations than the routes for Approach A, but they differ in the exact start nodes. Each Zone has one or more pick up stations from where the trip can start, but private car trips can start from any node within the zone. Therefore, the travel times for the base case have a higher variance from 04:30 to 08:40 minutes and are with 6:30 minutes slightly lower in average. The variance in time can be explained with higher discrepancy in distance, because more possible start nodes exist within a zone. Consequently, the travel speed is influenced

which directly influences the travel time. Quasi Maas in vehicle times show a lower variance because the path options are limited and can only take place between the train station and the pickup stations. They start with a minimum of 03:15 minutes, whereas 50% of the trips lie in between 04:05 minutes and 08:37 minutes. The longest in vehicle time can be expected with 11:00 minutes. Furthermore, the needed vehicles are computed by using an Add On called line blocking. For the car based scenario 33 vehicles are needed, whereas the van based scenario requires 24 vehicles to serve Centennial station.

5.2 Approach B - MaaS

For approach B, PTV Visum computes the optimal supply, which means that all trip requests are served. Furthermore, the necessary vehicles for various supply states as well as the resulting unserved demand are calculated. The results are displayed in Figure 18. They show that the unserved demand increases with a decrease of available vehicles. This effect is stronger for van-based cases because the seat capacity is higher. One van can pick up maximum seven different trip requests, whereas one car can pick up maximum 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.

If the vehicles would serve every trip, the detour and travel time would increase tremendously. This does not happen in the simulation because the detour factor is limited. To proof the impact of a higher detour factor, another simulation run is operated and the results are shown in the second half of this chapter. If the detour factor would not be limited, the travel times would increase and the passenger's contentment would fall. This would cause less utilization of the rideshare service due to lower service quality. PTV Visum does not allow to run the simulation without detour factor, so the impacts cannot be stated with certainty. Additionally, the occupancy rate of the operating vehicles can be extracted and information about the sharing behavior can be analyzed. Figure 19 shows the vehicle occupancy for each supply state and vehicle type.

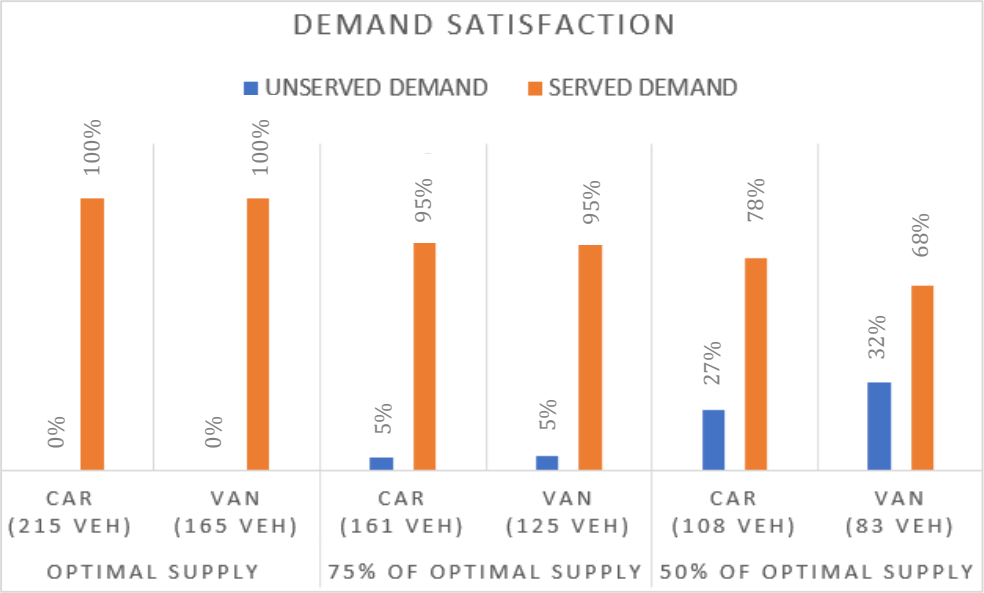
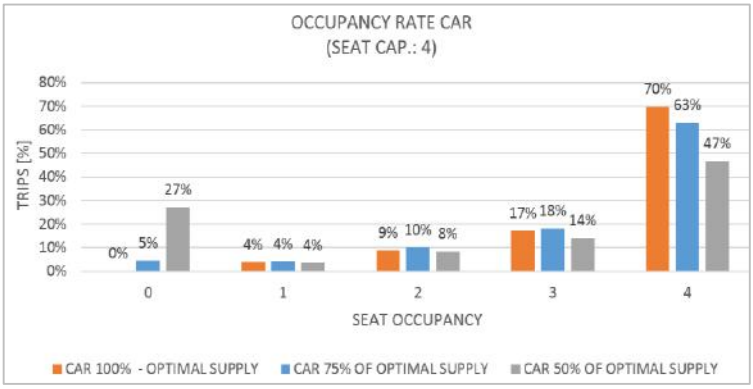


Figure 18 Demand Satisfaction Maas (detour factor 1.5)

Unserved trips are included in the bars with zero seat occupancy. Comparing car-based and van-based scenario, the share of occupancy develops in the same pattern for all supply states. The pattern is that the 75% optimal supply scenario counts almost always the most trips per seat occupancy rate followed from optimal supply and 50% of optimal supply case. Just for vehicles with zero or full occupancy this order changes and 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 less vehicles are available. The expected behavior would have been a higher occupancy when less vehicles are available to serve more requests. This examined phenomenon is explicable 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.



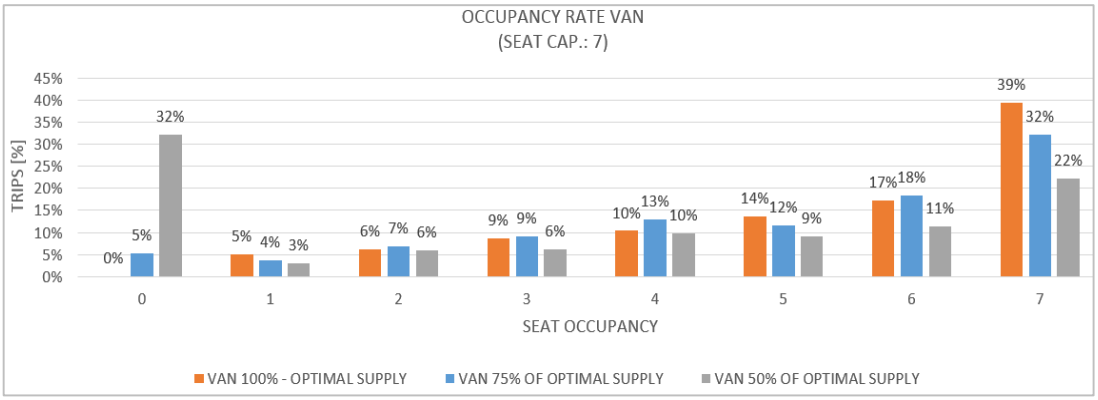


Figure 19 Occupancy Rate of Maas (detour factor 1.5)

The algorithm plans the tours concerning the known requests in the most efficient way with regards to the parameters like detour factor and maximum detour time, fleet size and seat capacity. Requests are selected depending on the effect they would have for the whole tour. That means if a request would cause a high negative effect for the whole tour, it is not included and can be included in a different tour of another vehicle with in the maximum wait time. As soon as the maximum waiting time has elapsed, the request is considered as unserved.

When reducing the number of vehicles, also the frequency is reduced. That means 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 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. The algorithm tries to plan all known requests in the most efficient way and builds tours. Trip requests which would cause high detour for vehicles and passengers are not regarded. The requests which are still open and are not causing high negative effects, are pooled in a way that passengers travel under almost equal conditions. According to that, the experienced detour factor and travel time is minimized. This explains the high rise of unserved demand and fall of full occupied vehicles when reducing from 75% to 50% of optimal supply, as well as the falling in vehicle time in Figure 20.

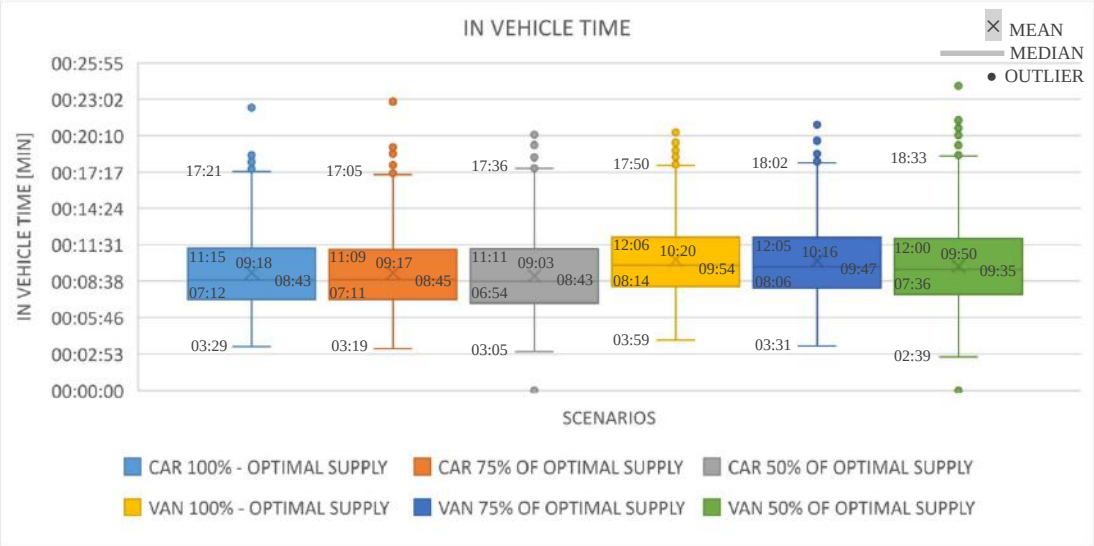


Figure 20 In Vehicle Time of MaaS (detour factor 1.5)

Approach B gives very detailed results such as the in vehicle time and origin wait time at the PUDO per supply state. The results are shown in boxplots and represent the analysis period from 7am to 10am. Outputs for in vehicle time are presented in Figure 20.

The main in vehicle time for car-based trips and optimal supply reaches 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 lower compared to the van-based optimal supply. This can result because of a higher occupancy rate per vehicle and is also the reason for the discrepancy between car and van-based 75% and 50% of optimal supply cases. The more trips requests are served per vehicle trip, the longer is the distance covered and the longer is the in vehicle time. Those values decrease slightly for 75% and 50% of optimal supply. The mean for those two cases lies between 09:17 and 09:03 minutes.

At the same time the in vehicle times have about the same duration, which states that the level of service regarding in vehicle time is hold equally. But 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 show like the car-based trips a slight increase of in-vehicle time with a decrease of available vehicles. For optimal supply, trip makers 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. Those values are stretched out from 08:06 to 12:05 minutes for the cases which use 75% of the optimal supply and 07:36 to 12:00 minutes for 50% of optimal supply. In general, the results are lower dispersed for the van-based scenarios.

Another important outcome is the origin wait time at the PUDO. It has a high influence on the total travel time and the passenger's mode choice. Results for approach B with a detour factor of 1.5 are shown in Figure 21. An increasing wait time can be detected with a decrease in available vehicles. Interesting to note is the slightly shorter wait time for van-based trips. Because vehicles are picking up most likely requests which are close to each other and vans can serve more passengers, the wait time decreases a little bit when compared to car-based trips. All measured wait times are within the maximum wait time of 15 minutes.

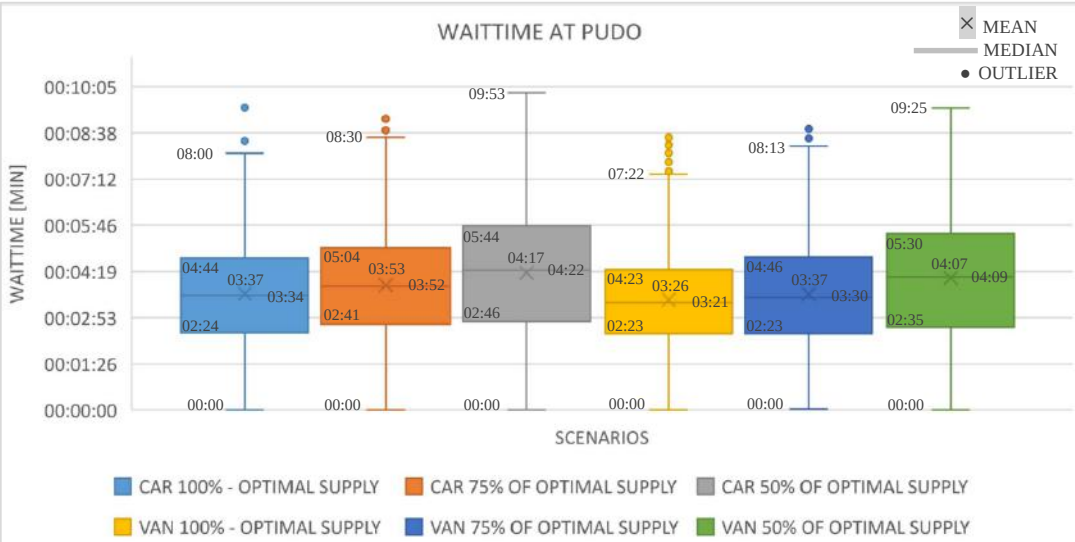


Figure 21 Origin Wait Time of MaaS (detour factor 1.5)

The first quartile of the car-based case with optimal supply has a very low wait time which lies between 0 and 02:24 minute. 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 vehicles 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. The less vehicles are on the road, the longer the passenger has to wait till he is picked up because the time till a vehicle is available is longer the fewer vehicles are available.

Regarding the results of Approach B, it can be said, that they are highly influenced by the detour factor. To examine this effect more detailed, another simulation is run with an increased

factor of five and maximum detour time of 60 minutes. The same fleet sizes as for the previous scenario are used for better comparison. Nevertheless, they are still titled as before, even though the optimal supply is slightly smaller.

Another important outcome is the number of unserved requests which is stated with 0 seats. 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. It can be said that 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 22.

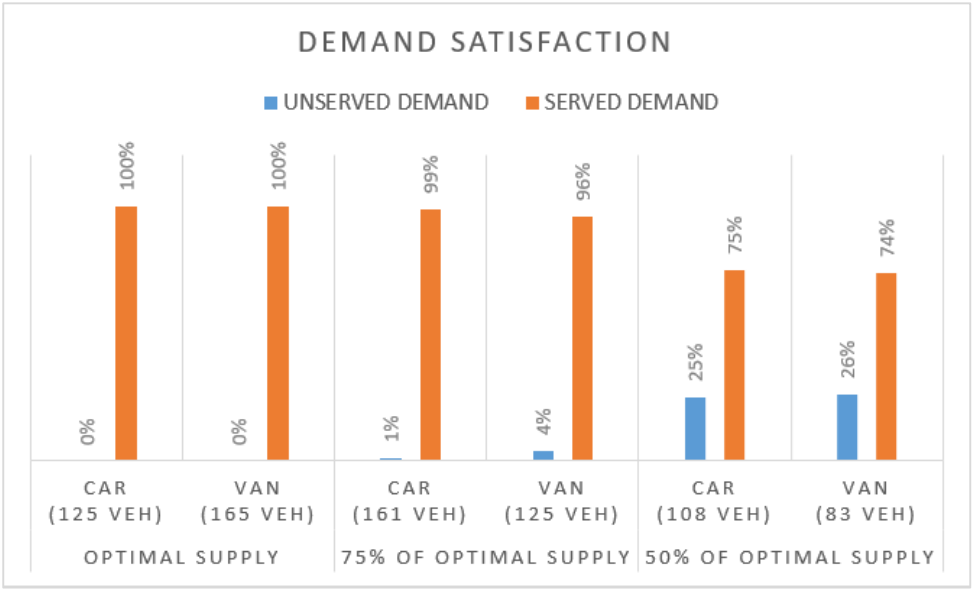


Figure 22 Demand Satisfaction MaaS (detour factor 5)

Like in the scenario with 1.5 detour factor, the number of vehicles with full occupancy decreases for all supply states when less vehicles are available. What is remarkable is, that the scenario with a detour factor of five, states a higher number of fully occupied vehicles. Accordingly, the detour factor affects a higher detour and therefore 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 very low amount of trips that are not fully occupied. The higher the occupancy the higher the amount of trips. Exact results are stated in Figure 23.

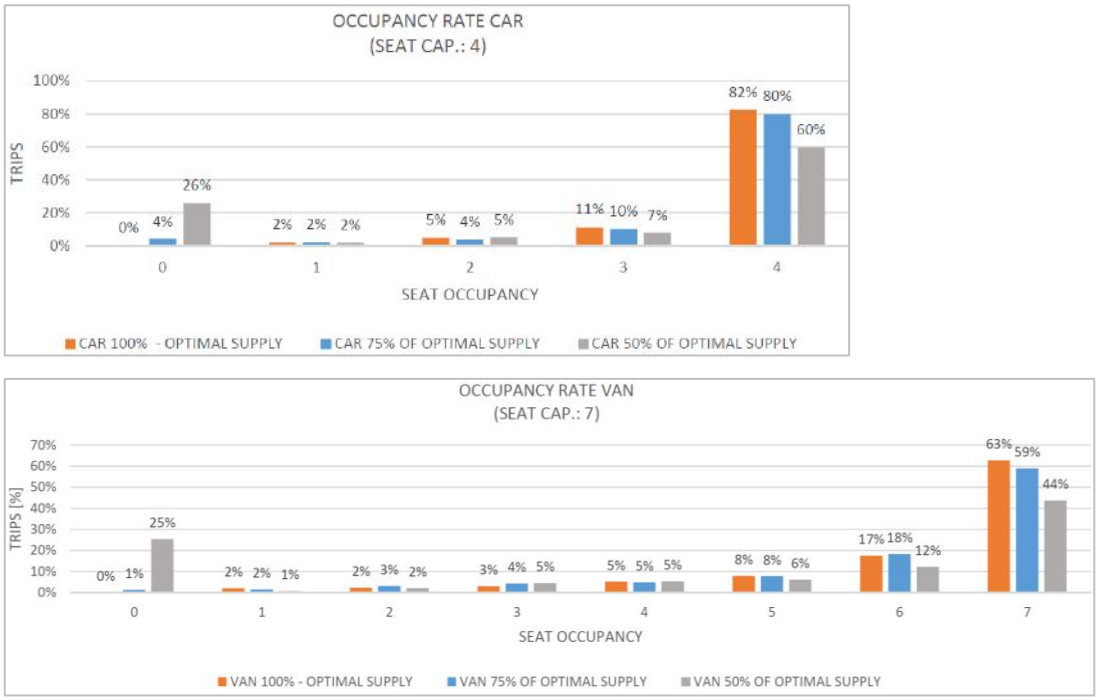


Figure 23 Occupancy Rate for MaaS (detour factor 5)

Additionally to the occupancy, also the in vehicle time is measured and the results are presented in Figure 24. It is directly noticeable that this scenario produces a lot of outliers above the maximum value. An outlier is an observation that lies outside the overall pattern of a distribution. In scientific studies, it can be an error in measurement and is usually a case which does not fit the model. In this case, the outliers are realistic and fit the model.

They show that many requests exceed the value of the majority of in vehicle time. This scenario uses a very high detour factor, which influences the maximum allowed detour and therefore trips with high in vehicle times are possible. Whereas in the scenario with a detour factor of 1.5 such durations are not allowed. Generally, the trend of mean in vehicle time is decreasing the smaller the tested fleet size.

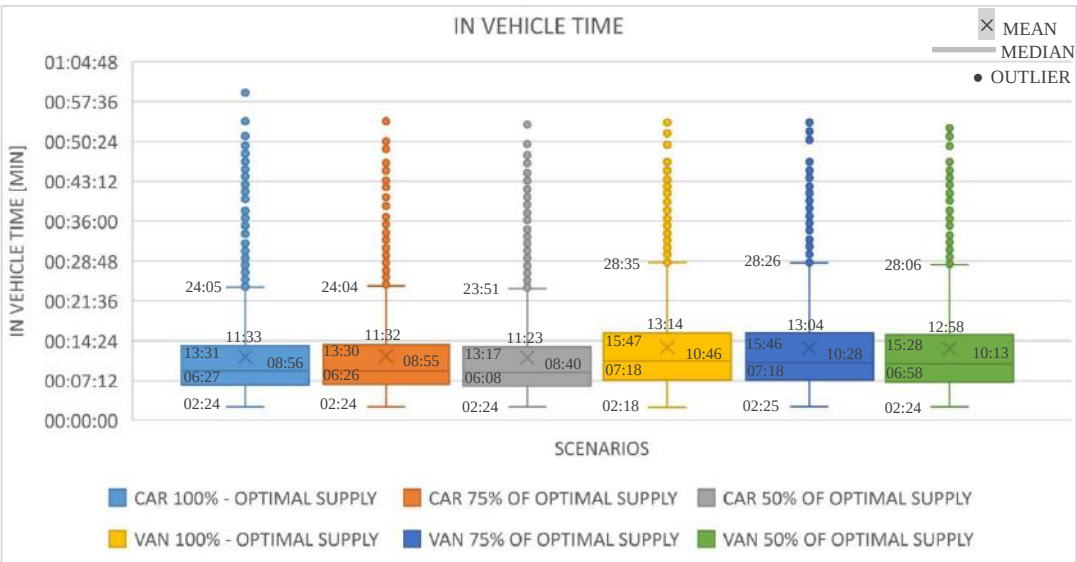


Figure 24 In Vehicle Time of MaaS (detour factor 5)

Comparing van and car-based scenarios, it is clearly visible that vans are about 01:30 minutes slower regarding the time the passenger spends in the vehicle. The dispersion of times is with about 7 minutes smaller for car-based scenarios looking at the second and third quartile than

for van-based scenarios with about 8 minutes. This effect is explicable with the different tour lengths. Since vans have a higher seat capacity, more passengers are picked up and therefore more requests within one tour are served. The outcome is a higher trips lengths and accordingly higher travel time. In general, it can be said, that the in vehicle time does not differ tremendously 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.

Additionally to the in vehicle time, the origin wait time is analyzed and shown in Figure 25. The origin wait time of passengers at their 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 one 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's wait time is in the range of 09:34 minutes and 15 minutes. The mean wait time is with 05:39 minutes about 40 seconds longer than the median with 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. 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.

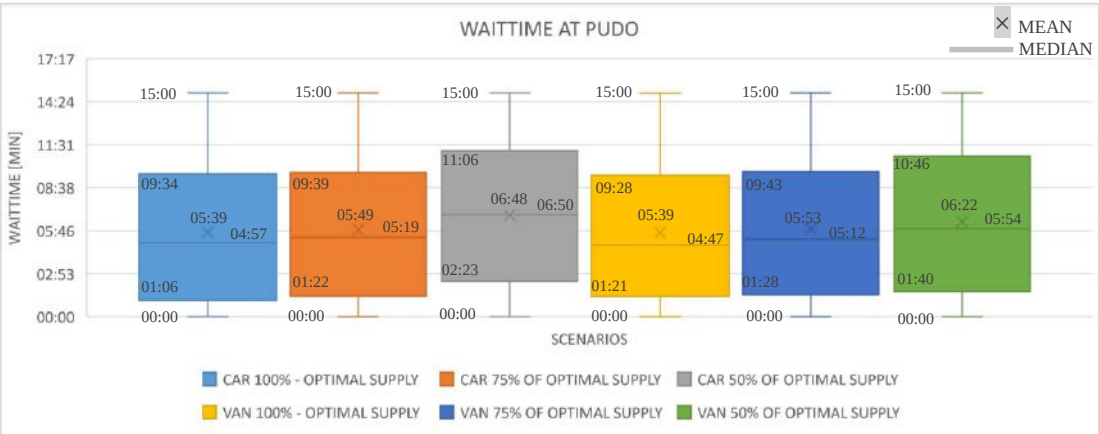


Figure 25 Origin Wait time of MaaS (detour factor 5)

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 05:39 minutes the same than 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 and the range of second and third quartile 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 requester 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.

In general, it can be said, that the stronger the increase of unserved requests the higher the growth in wait time. The less vehicles are on the road, the longer the passenger has to wait till he is picked up because the time till a vehicle is available is longer the fewer vehicles are available.

5.3 Comparative Results

Cost Analysis

In order to receive a meaningful analysis, the following paragraph is dedicated to the expected cost of approach A and B. We analyze the vehicle and driver costs which consist of different factors. To calculate an approximate cost for the vehicles, the traveled vehicle kilometers are multiplied depending on the vehicle size with 0.50 CAD/km for cars and 0.65 CAD/km for vans. Those amounts are standard values to calculate vehicle costs (29). Additionally, the driver cost is estimated, multiplying the number of necessary drivers by a salary of the simulation time. For three hours one driver earns 45 CAD which is the current minimum wage of the state of Ontario. As the final step, driver cost and vehicle cost are added up. Detailed results can be seen in Table 2.

The cheapest scenario is Approach A with vans as the operating vehicles. Approach A is only executed for one station and the values are estimated for the whole area which is not reasonable. Due to this reason also Approach A operating with cars is not considered in the final evaluation. The second least expensive scenario is Approach B, van-based, 50 % of optimal supply and a detour factor of 5 with a total cost of 6.558 CAD. Due to a higher seat capacity and therefore also fewer drivers the price is low.

Table 2 Cost analysis of Approach A and B

Scenario		Mode	Fleetsize [veh]	Kilometers Traveled [km]	Drivers needed [pers]	Wage/ 3h [CAD]	Driver Cost [CAD]	Cost/km [CAD]	Vehicle Cost [CAD]	Total Cost [CAD]
Approach A		Car	132	5096	132	45	5.940	0.5	2.548	8.488
Approach A		Van	96	3056	96		4.320	0.65	1.986	6.306
Approach B (Detourfactor 1.5)	Optimal Supply	Car	215	7826	215		9.675	0.5	3.913	13.588
Approach B (Detourfactor 1.5)	75% of optimal supply	Car	160	7705	160		7.200		3.853	11.053
Approach B (Detourfactor 1.5)	50% of optimal supply	Car	108	5746	108		4.860		2.873	7.733
Approach B (Detourfactor 1.5)	Optimal Supply	Van	165	6025	165		7.425	0.65	3.916	11.341
Approach B (Detourfactor 1.5)	75% of optimal supply	Van	125	5961	125		5.625		3.875	9.500
Approach B (Detourfactor 1.5)	50% of optimal supply	Van	83	4491	83		3.735		2.919	6.654
Approach B (Detourfactor 5)	Optimal Supply	Car	215	7615	215		9.675	0.5	3.807	13.482
Approach B (Detourfactor 5)	75% of optimal supply	Car	160	7805	160		7.200		3.903	11.103
Approach B (Detourfactor 5)	50% of optimal supply	Car	108	6000	108		4.860		3.000	7.860
Approach B (Detourfactor 5)	Optimal Supply	Van	165	5292	165		7.425	0.65	3.440	10.865
Approach B (Detourfactor 5)	75% of optimal supply	Van	125	5673	125		5.625		3.687	9.312
Approach B (Detourfactor 5)	50% of optimal supply	Van	83	4343	83		3.735		2.823	6.558

Additionally, less kilometers are traveled in total due to the high detour factor. Approach B operating with vans, 50% of optimal supply and a detour factor of 1.5 is following with a cost of 6.654 CAD. After, the car-based scenario with 50% of optimal supply and a detour factor of 1.5 states the third most economic option.

Regarding the color code of Table 2, the range goes from green to red with green being the cheapest scenario. A more detailed analysis regarding cost and additional valuation factors is shown in the next paragraph.

Comparative Analysis

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. The grey highlighted re-

sults are not included, because they do not have the same result types and cannot be compared with the other scenarios. In vehicle time and wait time are represented with the mean time of each case.

Three scenarios give very good results as they are evaluated with five or four pluses. The van-based scenario, with 75% of the optimal supply and detour
factor of 1.5 (marked with A), gives decent results and is very similar to the van-based scenario with 75% and detour factor of 5 (marked with C). Both are evaluated with four pluses. The scenario with 75% of optimal supply using cars and 1.5 detour factor (marked with B) shows the also very good results and is evaluated with five pluses.

Table 3 Comparative analysis of the scenarios

Scenario		Mode	Fleetsize [veh]		unserved demand [%]		Mean In Veh Time [min]		Mean Wait Time [min]		Total Cost [CAD]		Result	
Base Case		Car	1865	---	0%	+++	06:29	+++					+++	
Approach A		Car	132*	0	0%	+++	06:38	+++			6006.00		++++++	
		Van	96*	+	0%	+++	06:38	+++			6306.40		+++++++	
Approach B (Detourfactor 1.5)	Optimal Supply	Car	215	---	0%	+++	09:18	++	03:37	+	13588.00	---	0	
	75% of optimal supply		161	0	5%	+	09:17	++	03:53	0	11052.50	0	+++	
	50% of optimal supply		108	++	22%	-	09:03	+++	04:17	---	7733.00	++	+++	
	Optimal supply	Van	165	0	0%	+++	10:20	---	03:26	+++	11341.25	-	++	
	75% of optimal supply		125	++	5%	+	10:16	--	03:37	++	9499.65	+	++++	A
	50% of optimal supply		83	+++	32%	---	09:50	0	04:07	-	6654.15	+++	++	
Approach B (Detourfactor 5)	Optimal Supply	Car	215	---	0%	+++	11:33	+++	05:39	+++	13482.50	---	+++	
	75% of optimal supply		161	0	4%	+	11:39	++	05:49	++	11102.50	0	+++++	B
	50% of optimal supply		108	++	26%	--	11:23	+++	06:48	---	7860.00	++	++	
	Optimal Supply	Van	165	0	0%	+++	13:14	---	05:39	+++	10864.80	0	+++	
	75% of optimal supply		125	++	1%	++	13:04	--	05:53	+	9312.45	+	++++	C
	50% of optimal supply		83	+++	25%	--	12:58	-	06:22	0	6557.95	+++	+++	

*rough calculation for 4 stations
detailed results only available for one station

Regarding the fleet size, scenario A and C work with a smaller number of vehicles. Both are using 125 vans, whereas scenario B uses 161 cars. The prices for drivers and vehicles are calculated and included in the total cost. With only 1% of unserved requests, scenario C shows the best results followed from scenario B with 4% unserved requests and scenario A with 5% unserved demand. The category in vehicle is won by scenario A with 10:16 minutes. Scenario B states the second shortest time with 11:39 minutes and scenario C has the longest in vehicle time with 13:04 minutes. Also for the origin wait time scenario A gives the best results with 3:37 minutes. Scenario B and C are almost equal with 5:49 and 5:53 minutes wait time. Regarding the price, scenario C is the least expensive with operating cost of 9312.45 CAD, followed by scenario A with 9499.65 CAD and scenario B with 11102.5 CAD. Scenario A and C do not differ a lot because they have the same fleet size but the vehicles in scenario A are making more kilometers.

Summarizing those outcomes, it depends which outcome is seen as the most important. If the price is the most important characteristic, scenario A serves good results for a good price. The weakness for scenario A lies in the high number of unserved trips. In vehicle and wait time are very good and the shortest of all three scenarios. But if the service quality with regard to unserved trips has a higher importance, scenario C states a decent option. The weakness here is the high in vehicle and wait times. Scenario B presents the medium values for all characteristics, except the price which is the highest of the three scenarios. It can be seen as a good option regarding unserved demand, in vehicle and wait time. Additionally, it is evaluated with 5 pluses and can be seen as most decent option.

6 Conclusion and Future Work

As a conclusion, it can be said that this project is the base for evaluating the use of development planning applied to the City of Markham. Within the framework of a master thesis, it gives important findings regarding the mobility in Markham.

This study presents a detailed analysis of different approaches to solving first-mile transportation in Markham. In total, two approaches are created that differ in methodology. Approach A is carried out using a software tool of PTV Visum for public transport which means that the simulation runs with static routes and timetables that are manually created in 15 minute steps. Additionally, this approach is carried out first with 4 seated vehicles (car) and second with 7 seated vehicles (van) and the changes in travel time are compared. For Approach A, the results are good, but not representative because the software tool did not fit exactly to the intended objective. For this reason, approach B was created.

Approach B operates with a software tool of PTV Visum which is especially created to model on-demand service and is split in two main parts, whereas the first part operates with 4 seated vehicle (car) and the second part with 7 seated vehicles (van). Each of this parts is divided in three scenarios which are characterized by different fleet sizes and seat capacities. The optimal supply of vehicles to serve every trip request when operating with car respectively van is computed using an infinite fleet size as initial value. Based on the computed number of vehicles for the optimal supply, cases with 75% and 50% availability of optimal supply are created and examined regarding travel and wait time. During the analysis of the results it became clear that another simulation with a changed detour factor had to be made to get a better overview of the range and impact of the detour factor. Accordingly, to the number of needed vehicles and drivers, driven kilometers, as well as the quality of wait and travel time, all cases are rated regarding cost and benefits.

During the creation of the traffic system, used as a basis for the different approaches to examine travel and wait times, several points can be executed with more details. For example, a more comprehensive traffic volume data set would add a lot of value to the work. With that, the simulation can be modeled more accurately. Additionally, the results can be strengthened if real signal timings from Markham are included in the simulation. Since this simulation only models cars and vans, it can be an option to add pedestrians and cyclists, as well as heavy goods traffic and buses. That would make the model more realistic and authentic. With another survey which would contain a more detailed content about the trip pattern of commuters in Markham, more scenarios with variations of PUDO’s and with various fleet sizes can be examined. Moreover, it can be inspected, how the number of necessary vehicles for optimal supply varies, when depots are taken into account or when the vehicles only operate for one station and don’t interact with the other stations. Also the analyzed criteria can be changed. For example, attention can be paid to the changes in mode choice when a certain service, such as MaaS, is offered.

All in all it can be said, that this thesis is a good orientation when discussing about new options for public transit in Markham and gives an overview of what can be possible.

REFERENCES

(1) Statistics Canada, "Main Mode of Commuting, 2016 Census," 20 02 2019. (Online). Available: https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/dt-td/Rp-eng.cfm?APATH=3&DETAIL=0&DIM=0&FL=A&FREE=0&GC=0&GID=0&GK=0&GRP=1&LANG=E&PID=110713&PRID=10&PTYPE=109445&S=0&SHOWALL=0&SUB=0&THEME=125&Temporal=2016&VID=0&VNAMEE=&VNAMEF=. (Accessed: 26 02 2019).

(2) J.D´Inca,www.forbes.com, "What The Future Of Mobility Means For Today's Transportation Industry," 18 11 2016. (Online). Available: https://www.forbes.com/sites/oliverwyman/2016/11/17/what-the-future-of-mobility-means-for-todays-transportation-industry/#151fee0f22d4. (Accessed: 20 11 2018).

(3) RideCo, 2019. (Online). Available:https://www.rideco.com/tech/what-we-do#success_stories. (Accessed: 20 05 2019).

(4) Statistics Canada, "Focus on Geography Series, 2011 Census," 2016. (Online). Available: https://www12.statcan.gc.ca/census-recensement/2011/as-sa/fogs-spg/Facts-csd-eng.cfm?LANG=Eng&GK=CSD&GC=3520005 (Accessed: 05 03 2019).

(5) Statistics Canada, "Focus on Geography Series, 2011 Census," 2016. (Online). Available: https://www12.statcan.gc.ca/census-recensement/2011/as-sa/fogs-spg/Facts-csd-eng.cfm?LANG=Eng&GK=CSD&GC=3519036 (Accessed: 05 03 2019)

(6) Epomm.eu, 2019. (Online). Available: http://www.epomm.eu/newsletter/v2/eupdate.php?nl=1217_2&lan=en. (Accessed: 29 03 2019).

(7) "What is MaaS? — MAAS-Alliance", MAAS-Alliance, 2019. (Online). Available: https://maas-alliance.eu/homepage/what-is-maas/. (Accessed: 29 03 2019).

(8) "What is Mobility as a Service (MaaS)? - MaaS Global", MaaS Global, 2019. (Online). Available: https://maas.global/what-is-mobility-as-a-service-maas/. (Accessed: 29 03 2019).

(9) "Ride-sharing | Definition of ride-sharing in English by Oxford Dictionaries", Oxford Dictionaries | English, 2019. (Online). Available: https://en.oxforddictionaries.com/definition/ride-sharing. (Accessed: 02 04 2019).

(10) Solving the first mile-lastmile on-demand," *RideCo*, 03 2018. (Online). Available: https://docsend.com/view/wktxxms. (Accessed: 03 04 2019).

(11) Statistics Canada, "2016 Census of Population, Catalogue no. 98-404-X2016001", 29 11 2017. (Online). Available: https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/page.cfm?Lang=E&Geo1=CSD&Code1=3512005&Geo2=CD&Code2=3512&Data=Count&SearchText=belleville&SearchType=Begins&SearchPR=01&B1=Population&TABID=1. (Accessed: 09 01 2019).

(12) C. o. Belleville, "City of Belleville," (Online). Available: http://belleville.ca/city-hall/page/transit. (Accessed: 09 01 2019).

(13) D. R. Corrigan, „The Ontario Educational Communications Authority (TVO)," 17 10 2018. (Online). Available: https://www.tvo.org/article/current-affairs/what-happens-when-ride-sharing-meets-public-transit. (Accessed: 09 01 2019).

(14) Simply Analytics, „simplyanalytics.com,“ (Online). Available: http://app.simplyanalytics.com.ezproxy.lib.ryerson.ca/index.html. (Accessed: 12 11 2018).

(15) P. Pentikainen, “Demand-Responsive Transit in Innisfil,“ 15 06 2016. (Online). Available: https://innisfil.civicweb.net/FileStorage/C7117E87A760491EA B2A3F7EDBF9AF79-DemandResponsive%20Transit%20in%20Innisfil.pdf. (Accessed: 09 01 2019)

(16) R. Cayford and Y. B. Y. Yim, “Personalized Demand-Responsive Transit Service, “ 01 04 2004. (Online). Available: https://escholarship.org/uc/item/29j111ts. (Accessed: 09 01 2019).

(17) MVG, “MVG IsarTiger,” Mvg.de, 2019. (Online). Available: https://www.mvg.de/services/mobile-services/mvg-isartiger.html. (Accessed: 19 03 2019).
RideCo, 2019. (Online). Available :https://www.rideco.com/tech/what-we-do#success_stories. (Accessed: 20 05 2019).

(18) Tom V. Mathew and K V Krishna Rao, “Introduction to Transportation Engineering, Chapter 10 Traffic Assignment,” 07 05 2007. (Online) Available: https://nptel.ac.in/courses/105101087/downloads/Lec-10.pdf

(19) Y. Sheffi and W. Powell, “A Comparison of Stochastic and Deterministic Traffic Assignment over Congested Networks,” Transportation Research Part B: Methodological, Vol. 15, issue 1, p. 53-64, 02 2005. (Online). Available: https://www.sciencedirect.com/science/article/pii/0191261581900461. (Accessed: 21 03 2019)

(20) Highway Capacity Manual. Washington, D.C.: Transportation Research Board of the National Academies, 2000.

(21) M. Venigalla, “Module 6 Traffic Assignment, Stochastic Assignment,” 30 03 2015. (Video File). Available: https://www.youtube.com/watch?v=I-0in2ZWIIk. (Accessed: 21 03 2019).

(22) P. Savolainen, “Lecture 04 Traffic Assignment,” 23 08 2015. (Video File). Available: https://www.youtube.com/watch?v=qjSLM3-ENxU (Accessed: 06 03 2019).

(23) B. Farooq, Topic: “Introduction to Dynamic Traffic Assignment,” CE 392D, Ryerson University Toronto/Department of Civil Engineering, Canada, 22 01 2018. (University Lecture)

(24) “About Markham,” markham.ca, (Online). Available:https://www.markham.ca/wps/portal/Markham/AboutMarkham/FactsStats/!ut/p/a1/jZFNU4MwEIZ_iweOki3hS28ptGlohYKl0lwccJAyg6R DUcZ_38hw6YyN7i2Z58m7u0EcZYi3Vdd5X0t2rz5OXP71XQT4i1DiJdb4wHYwl9hRiMM4EjgIAG4UQR GP2Dg zcgaAneRWEAivJv7JDCAGpOvAMb8iHreZu_GRmICMObvrdCPZ24C. (Accessed: 20 11 2018).

(25) SimplyAnalytics, Inc., (Online) Available: https://simplyanalytics.com/ (Accessed: 09 01 2019).

(26) "GO Transit | Regional Public Transit Service for the GTHA," Gotransit.com, 2019. (Online). Available: https://www.gotransit.com/. (Accessed: 19 03 2019).

(27) “Transportation Tomorrow Survey 2016 “, (Online). Available: http://www.tts2016.ca/en/. (Accessed: 31 12 2018).

(28) Data Management Group, University of Toronto, “Cordon Count Program,” http://dmg.utoronto.ca, (Online).
Available: http://dmg.utoronto.ca/cordon-count/cc-reports
(Accessed: 05 01 2019).

(29) B. Farooq, (Private Communication). 06 03 2019

1