OPTIMIZING TRUCK PARKING FACILITIES WITH MAJOR DISTRIBUTION CENTRES IN PANDEMIC CONDITIONS

ELANAKAYON ANNALINGAM

A THESIS SUBMITTED TO
THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
MASTER OF APPLIED SCIENCE IN CIVIL ENGINEERING

GRADUATE PROGRAM IN CIVIL ENGINEERING
YORK UNIVERSITY
TORONTO, ON

December 2023

ABSTRACT

The Covid-19 pandemic has had a disproportionate impact on truck drivers facing inadequate rest space availability due to exacerbated by pandemic conditions. GPS data is used in this thesis to understand trends of freight parking and the critical locations in which freight activity is occurring. The data is also used to compare pre-pandemic patterns in 2019 with pandemic conditions in 2020.

An optimization scheme is developed using a P-median approach to optimize travel from rest areas to major distribution centres. This scheme identifies the best locations where truck drivers can park and rest before accessing distribution centres. It is also proposed to be used to identify top locations for potential expansion for rest areas. The Region of Peel is used as the study area for this analysis as a major freight centre and documented impact from the Covid-19 pandemic.

ACKNOWLEDGEMENTS

I want to first show gratitude to my two supervisors for this master's program. Both Dr. Peter Y. Park and Dr. Kevin Gingerich have provided me with an introduction to the fields of transportation engineering and transportation planning that instilled an interest in the pursuit of this graduate degree. I want to thank them for their additional support in instruction, review, and guidance over these past years as a graduate student. Dr. Park provided overarching support for this degree and provided crucial instruction on the presentation of research from a holistic approach. Dr. Gingerich provided support in ensuring that the details of this thesis met the expected academic standard. He also pre-processed the GPS data to aggregate the GPS pings into truck stops that became the basis for the analysis. The process for this master's program took longer than expected so I appreciate their continued patience and belief.

I want to extend appreciation towards Transport Canada who first provided an opportunity to pursue research on pandemic impacts on freight. I want to thank the Region of Peel and its member municipalities who provided support in interest of this research and provided information and supporting data that aided in analysis. The Smart Freight Centre organized by the Region also allowed for continued study of the pandemic impacts on freight. The Centre also facilitated partnerships with other institutions including the University of Toronto, Toronto Metropolitan University, and McMaster University. Through these partnerships, the data needed for this thesis was acquired and in particular the University of Toronto's Data Management Group provided direct support.

I want to extend my appreciation to my fellow graduate students in the civil engineering program. I want to particularly thank Ucchas, Soha, Yashar, Ubaid, Ahmad, Tanvir and Tim whom I spent my time with on campus before the pandemic hit. You provided friendship and support that contributed positively to my graduate student experience. I want to thank Ariel Yerushalmi who aided the parking bylaw analysis as an undergraduate research assistant. I want to thank the faculty members who provided support and instruction these past years, including Dr. Mehdi Nourinejad, Dr. Manos Papagelis, Dr. Usman Khan, and Dr. Terry Sachlos. I want to express thanks to Sindy Mahal for also providing administrative support throughout all these years. I also want to thank the ITE York University Student Chapter for providing me with extra-curricular experience that augmented my academic journey.

I want to extend my deepest gratitude and appreciation to my friends and family. My friends have shown interest in this academic process while also allowing me to pursue interests outside of academics. My younger brother has been a major support these past few years and I appreciate the additional support he provided to my parents. My late father has supported me my entire life and continued to do so even with severe illness and that will always be appreciated. Finally, I want to thank my mother who has been my most supportive figure. Through her aid, interest, and support through these past four years, I was able to work through this degree and I want to thank her for providing me the opportunity to pursue my academic interests.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1 Covid-19 Pandemic

The emergence of a pandemic caused by Covid-19 has led to various societal shifts in behaviour and consequences for health and safety. Transportation patterns have changed during and after public health lockdown measures imposed by governments since March 2020. For example, vehicular trips were estimated to have declined 40 percent on Highway 401 in Southern Ontario at the onset of the pandemic in late March 2020 (Stone, 2020). The pandemic has been ongoing for over two years, and traffic has only recovered 80% of pre-pandemic conditions in high-traffic zones like Downtown Toronto (Harvey, 2022).

Truck traffic during the pandemic remained relatively steady and has continued to supply essential services to industries such as hospitals, pharmacies, grocery stores, and gas stations (Government of Canada, 2021). Cross-border travel of private vehicles or nonessential travel was reduced by 75-85% (depending on residency/citizenship status) in 2020 compared to 2019. Still, essential travel that includes truck drivers was only reduced by 25%. The necessary demand for imports/exports has allowed the border to remain open for these workers (Government of Canada, 2021).

The Government of Ontario lists 17 essential workplaces during the pandemic. The list includes industries that involve supply chains and transportation services, underscoring the importance of maintaining supply chain and logistics operations during various phases of a pandemic shutdown (Government of Ontario, 2020). The workers within these industries are prone to Covid-19, which can lead to significant health implications (Region of Peel, 2021a).

Additional waves of Covid-19 spread were observed in Ontario and elsewhere worldwide. Variants of the virus also spread after the first wave and extended the duration of the pandemic. Some of the impacts of Covid-19 will be permanent and transformational as a "new normal" emerges (Kim, 2021). Therefore robust, resilient, and safe processes, procedures, and strategies are needed to adapt, maintain, and operate efficient supply chains and logistics.

1.2 Region of Peel Freight Activities

The transportation impacts of the pandemic are magnified in areas with substantial passenger and freight trips. This thesis focuses on the Region of Peel, a regional municipality in Canada representing the cities of Mississauga and Brampton and the town of Caledon. The Region is located immediately west of the City of Toronto and is part of the Greater Toronto Area. Toronto-Pearson International Airport is also situated alongside its border with Toronto and represents the largest airport in the country (GTAA, 2020).

Approximately 2 billion dollars worth of goods are moved through the east-west highways in the Region of Peel daily (Ministry of Transportation, 2014, as cited in Region of Peel, 2017). Since every 4 out of 9 jobs within the Region is related to freight, the goods movement industry generates \$29 billion of labour income (Region of Peel, 2017). Toronto-Pearson International Airport is the largest air cargo facility in the country. The amount of air cargo at this location is more than the sum of air cargo between the second and third-largest airports of Vancouver and Montreal (Region of Peel, 2017). The Region's good movement industry produced \$49 billion in Gross Domestic Product (GDP), representing 21.1 percent of the provincial goods movement GDP and 8.7 percent of the national goods movement GDP (Region of Peel 2015, as cited in Region of Peel 2017).

The commodity flow in the Region of Peel significantly impacts the national economy, and identifying critical locations of freight activity is needed to improve infrastructure for economic benefit (Lightstone & Duggal, 2017). The Region of Peel has implemented initiatives such as the Off-Peak Delivery program and developed proactive strategies to anticipate and implement emerging freight trends and technology (Region of Peel, 2017). As such, the Region of Peel is chosen as the study area for its potential in practical research regarding Canadian freight activity.

As a major centre for freight activity, freight-related facilities are also present within the region. Distribution centres serve as hubs for the exchange of goods between firms. Many trucks also stop at rest areas to support short breaks or longer breaks to meet hours of service regulations and reduce fatigue. Truck drivers are categorized by their workload as long-haul or short-haul drivers. Long-haul drivers transport goods by travelling long distances to deliver goods from locality to locality. They perform limited trips within a local area. Short-haul drivers work within a locality and exchange goods at retail or last-mile locations. Both types of drivers access both types of facilities and represent an essential workforce for the region, but this study will focus on long-haul drivers.

1.3 Study Goals and Objectives

An area of interest in the supply chain and logistics industry is the ability of truck drivers to find adequate rest space for long-haul trips with proximity to nearby distribution centres where many deliveries are located. These are vital locations yet result in frequent contact points between other people. Countermeasures are proposed to mitigate the spread of a pandemic virus when truck drivers are stopped at these facilities.

The pandemic has led to the implementation of public health measures that impacted the ability of truck drivers to conduct their work at distribution centres. For example, some facilities have implemented an appointment-type parking system that reduces parking duration for trucks within their facilities. This approach limits the ability of trucks to access distribution centres before the exchange, leading to truck drivers finding alternative spaces to park close to the distribution centre if possible. This lack of parking supply leads to crowding in parking areas and poses a public health concern. Examining facilities of high demand is essential to determine critical locations for potential improvement with the limited resources for available parking (Lightstone & Duggal, 2017).

A public health issue occurs as some establishments limit drivers' access to washrooms and cleaning supplies, leading to drivers finding relief in unhygienic locations (Walsh, 2020). This research will aim to determine the facilities that may face these restrictions due to frequent usage and propose mitigation strategies to minimize these issues. This research aims to identify spatial and temporal changes to long-haul truck patterns during the onset of the Covid-19 pandemic and provide pre-emptive allocation strategies of truck rest facilities to minimize Covid-19 spread at major distribution centres (MDCs).

Truck drivers often face difficulties accessing rest area space before travelling to distribution centres. The pandemic has accelerated the problem as firms impose restrictions that limit proximity to truck drivers during deliveries. Spatial and temporal analysis applied to GPS data provide insights into the parking patterns within the Region of Peel. An optimization technique is used to minimize the travel time between these groups of facilities so that the travel experience is improved for these workers. This process allows for the identification and prioritization of the facilities that truck drivers can access before travelling to major distribution centres, especially under limited conditions. The objectives of the research are listed as follows:

1. Identify major distribution centres (MDCs) and major rest areas (MRAs) for trucks in the study area,
2. Examine the spatial pattern of long-haul truck stops before the Covid-19 pandemic in 2019 and at the onset of the pandemic in 2020,
3. Process and analyze the truck trips travelling from rest area facilities to major distribution centres,
4. Prioritize MRA locations during a pandemic using optimization techniques.

This research output utilizes ATRI (American Transportation Research Institute) GPS data in analyzing truck parking activities. An allocation strategy is presented as a tool to mitigate pandemic spread to protect truck drivers by identifying key locations where limited resources such as disinfectant are needed.

1.4 Scope

The study area is the Region of Peel. The Region represents a major freight hub within Canada and is contiguous with the western border of Toronto, the country's largest city. The cities of Mississauga and Brampton, as well as the town of Caledon, make up the municipalities in the region. Toronto's Pearson International Airport is located within Mississauga, with the logistics industry nearby. The airport represents the country's most prominent air travel facility and a central hub for international goods movement (GTAA, 2020).

This thesis focuses on long-haul trips or trucking trips of considerable distance exchanging goods at distribution centres. In other words, the study does not examine short-haul trips or local-based trucking trips between warehouses and retail locations. As such, the data is representative of trips arriving at the study area from neighbouring municipalities, the rest of Ontario, the rest of Canada, and cross-border travel with the United States. For example, Highway 401 and Queen Elizabeth Way provide freeway infrastructure for crucial border crossings in northeastern Michigan State and northwestern New York State.

GPS data is obtained for one and a half years from 2019 and 2020. The 2019 year is used to demonstrate the pre-pandemic truck trip patterns. The 2020 year provides evidence of changes to the truck trip patterns at the onset of the pandemic scenario. Data beyond this time period is beyond the scope of the thesis. The available time period ranges from January 2019 to July 2020 inclusive. However, the month of January 2020 and the months of August-December 2020 are not available in the dataset. Due to the difference in data available for particular months between each year, comparisons between years will be based on February through July in 2019 and 2020.

1.5 Thesis Structure

This research thesis is organized into seven chapters. In Chapter 2: Literature Review, a literature review is presented to provide a background to the ongoing Covid-19 pandemic, its impact on freight and freight facilities, GPS and spatial analysis in freight facilities and location-allocation problems.

Further issues within freight parking are also discussed. Chapter 3: Study Area and Data will present the Region of Peel as a freight centre, the GPS data used within this thesis, and a preliminary list of rest areas and distribution centres. Chapter 4: Methods of Analysis will provide an outline of the analysis applied with the GPS data to achieve the objectives of this thesis. The tools used to conduct the analysis and the zones used for each output will be contextualized. Chapter 5: Pandemic impact on Truck Parking Patterns will present the truck parking patterns will be presented for both study years. The major distribution centres and major rest area facilities are also identified. The trips between the two types of firms are identified. In other words, the results of objectives one, two and three are presented here. In Chapter 6: Optimization of Parking Facilities, the optimization of travel between rest area facilities and major distribution centres is conducted. As such, this chapter will present the results of objectives three and four. In Chapter 7: Conclusion, the thesis results will be summarized and presented with context on the application of this output to improve freight parking in pandemic conditions.

CHAPTER 2: LITERATURE REVIEW

2.1 Covid-19 Pandemic and Freight Implications

The Covid-19 pandemic has impacted aspects of society. It is a viral respiratory disease with elevated risks of severe outcomes that can lead to hospitalization and death. The virus (SARS-Cov-2) is spread through air droplets expelled by infected persons and inhaled by uninfected individuals (CDC, 2021). The spread is so prevalent that it has created extensive disruptions in society. Specific industries have been designated worldwide as essential for operation under these pandemic conditions. For example, O Reg. 82/20 in Ontario listed supply chain and transportation industries as two of the nineteen categories of essential occupations (Government of Ontario, 2020). It is therefore important to review the impact of this pandemic on the freight industry.

Health profiles of truck drivers consistently note the greater risk of more severe outcomes from Covid-19 infection compared to the general populace. Truck drivers within the United States of America have a median age of 49, with increased age being a risk factor for poor outcomes with Covid-19 infection (Costello & Suarez, 2015, Ionaddis et al., 2020, as cited in Lemke et al., 2020). Truck drivers also possess comorbidities attributed to increased risk, such as obesity, diabetes, and other metabolic and respiratory illnesses (Bachmann et al., 2018, Apostolopoulos et al., 2016, Birdsey et al., 2015, Bhatia et al., 1998, Benstowe, 2008, Dahl et al., 2009, Sieber et al., 2014, and Kreuger et al., 2007, as cited in Lemke et al., 2020).

A characteristic of Covid-19 is the ability to transfer infection through community spread. Community spread refers to cases of illness in which the source of infection is attributed to the community at large. A review of Covid-19 cases within Uganda conducted at the onset of the pandemic indicated that long-haul truck drivers were associated with 72 percent of patient cases identified from limited testing (Bajunirwe et al., 2020). Contract tracing of cases within the community indicates that truck driver cases increase the spread of the virus in the region. These drivers drive long distances with extensive contacts within their employment network due to international travel (Bajunirwe et al., 2020). Although the health profiles of drivers within the Region of Peel may differ, there is an expectation of similar extensive contacts that increase potential spread. The Region of Peel has noted that truck drivers represent 2000 cases from the period of March 2020 to May 2021. Similar to the Uganda case study, a large proportion of patients are attributed to some cross-border international travel between Canada and the United States, representing 57% of these cases. (Region of Peel, 2021a).

2.2 Safety Concerns with Freight Parking

2.2.1 Fatigue Collisions

Freight drivers may become fatigued when completing their work activities. When drivers experience fatigue, they increase the risk of collisions that endanger their health and those around them. A discussion of fatigue collisions is given in this section to emphasize the importance of truck rest areas for the safety of all road users.

A strict classification of fatigue collisions is given by Banerjee et al. (2009) as those that are specifically attributed to driver fatigue. An expanded classification of fatigue collisions includes extra consideration from external factors such as the driver not being at fault or the vehicle not experiencing damage (Banerjee et al., 2009). For both the strict and expanded classification, collisions occur 30 miles or more away from a rest stop facility (Banerjee et al., 2009). The increased collision rate may indicate the effect of the driver's inability to find adequate parking space.

Bunn et al. (2017) examined freight vehicle collisions caused by driver fatigue and other factors. Through a binomial logit-based approach, specific factors were associated with identifying fatigue and non-fatigue collisions. These factors include collisions that occur during the nighttime, collisions that are 20 miles or more away from a rest area, and collisions that involve a single vehicle. An analysis showed that further increases in risk occur at more considerable distances away from rest areas, with a distance greater than 40 miles exhibiting seven times more risk compared to non-fatigue collisions associated with collisions less than 20 miles away (Bunn et al., 2017). This distance range may differ based on the jurisdiction. In Saskatchewan, an optimal distance of 250 kilometres was suggested by long-haul drivers to address their travel demand through a survey-based analysis (Crizzle et al., 2020).

2.2.2 Hours of Service for Truck Drivers

Hours of service regulations refer to the restrictions placed on the amount of working time a truck driver can perform in a given time period. In Canada, drivers are not allowed to drive after 14 hours of work activities, of which 13 hours can be driving activity. This time period is called on-duty time. After working those hours, drivers must rest for 10 hours with a mandatory 8-hour consecutive period of rest. This time period is called off-duty time. Further regulations dictate weekly or biweekly restrictions. These regulations ensure that drivers are adequately rested before they perform additional work to combat fatigue-related collisions. To meet regulations, drivers must document their time spent on work activity (Motor Transport Act, 2019).

However, these regulations presume that a rest area is always available for drivers to sleep in a safe and accessible environment with amenities to maintain general well-being (food, washrooms, etc.). These regulations also may induce dangerous situations if drivers cannot find a stop to rest, especially in remote areas. A hypothetical example by Mclean (2016) illustrates a driver planning to stop at a 24-hour restaurant and satisfy the on-duty hour requirements. However, an unexpected closure forces the driver to choose an alternative restaurant an hour away. The driver may take a further detour to avoid an inspection site, leading to a compounded risk of a fatigue-related collision (Mclean, 2016). The presence of the hours of service regulations may lead to riskier decision-making from this driver especially where there is an insufficient truck parking supply nearby.

The enforcement of hours of service can lead to drivers fabricating their on-duty and off-duty hours to meet regulations. However, implementing electronic logging devices or ELDs prevents these activities from occurring. These devices are electronic control modules placed within trucks that aid in logging on-duty and off-duty hours. These devices aim to reduce driver fatigue-related collisions through stricter adherence to hours of service. In Canada, the enforcement of ELDs with fines for breaches started on January 1st, 2023, but these devices have been used within the industry for years (Motor Transport Act, 2019). The US has been enforcing the use of ELDs since 2017 (FMCSA, 2022). When considering scenarios like the one mentioned in Mclean (2016), drivers' behaviour may change due to an active logging system tracking their travel. Sufficient and safe rest areas are needed to address the increased demand for adherence and allow drivers to meet regulations.

2.3 Availability of Freight Parking Facilities

Freight parking facilities are needed to address the demand from drivers looking for space to park and rest during off-duty hours. Assessing and identifying the pre-existing facilities is essential to reduce the need for costly new facilities.

2.3.1 Identification of Parking Facilities

Freight drivers use a variety of locations to park. These areas may or may not be conventional rest areas. Drivers may face situations where they park in unauthorized areas. Nevland et al. (2020) developed a classification scheme for truck parking based on GPS data of truck parking stops within the Region of Peel. After identifying land parcels with significant freight parking activity, variables associated with the property were used to develop a scheme to classify the area. Some of these variables include the type of industry for the parcel, the presence of a weigh station, the zoning type of the parcel, the size of the parcel in comparison to the available road length, the amount of building footprint, the presence of crucial roadway segments such as highway ramps, and parking infraction data to help differentiate between authorized and authorized parking (Nevland et al., 2020). The categories for classification include rest areas and gas stations, weigh stations, publicly accessible truck parking, privately accessible truck parking, legal roadside parking, illegal roadside parking, illegal highway ramp parking, illegal parking on public property, and illegal parking on private property.

Jung and Oh (2017) proposed using supplemental rest areas in Korea. This infrastructure is a small-scale rest area just off a major roadway that is supplemental to typical rest area facilities. Within a freeway application, these areas will be accessed through ramps with corresponding exit ramps to re-enter the freeway. Through a safety performance function (SPF) based analysis, these facilities provide a 14 percent reduction in fatigue-related collisions and a 36 percent reduction in truck collisions on-ramp roadways (Jung & Oh, 2017). Within southern Ontario, similar types of facilities are called OnRoute. These facilities are highway rest areas that provide amenities and services and are located on Highway 401 and 400. However, these facilities are open to the general public, but dedicated parking for truck drivers exists. The Region of Peel also does not currently possess this type of facility (OnRoute, 2022).

2.3.2 Supply Issues for Rest Area Facilities

American drivers have reported that 80 percent of rest areas were full, leading to these drivers parking in illegal parking locations (such as freeway ramps and shoulders and private locations). The overnight period past 10 p.m. is identified for this level of shortage (Davis, 1997). A study conducted by Chatterjee & Wegmann (2000) also showed that 28% of drivers use freeway ramps and shoulders during an overnight period from 10 p.m. to 6 a.m. due to the lack of supply of appropriate rest area facilities they can park in. However, caution may be placed on universal solutions to address supply, as some regions may have varying demand levels for rest area facilities (Garber & Wang, 2004).

A Canadian study in Saskatchewan showed drivers face issues accessing rest area facilities with adequate amenities. Drivers want consistent access to rest area facilities, including sufficient bathrooms, running water, and showers (Crizzle et al., 2020).

Paid parking is an approach to addressing some of the issues with supply if parking demand is high. A survey-based approach to understanding the need for priced reservation of stops at rest area facilities indicated that 48.2 percent of truck drivers are unwilling to pay to reserve parking spaces. However, 48.8 percent of truck drivers prefer a reservation-type system in major metropolitan areas, with long-haul drivers more willing to pay for such a system (Boris & Johnson, 2015).

2.4 Spatial Analysis using GPS Information

2.4.1 Parking Dwell Time

GPS data is a popular source of information to identify and classify truck parking events, but it often requires data processing. The unprocessed raw data provides a series of pings providing the truck's ID, location, date, and time at various points along the trip. This information is used to estimate parking dwell time to determine how long a freight vehicle has parked within a location. Some studies use a maximum speed threshold to define dwell time when a truck is stationary. Yang et al. (2014) used speeds between 0 and 14 km/h as part of a stopping speed. Consecutive pings that met this benchmark with a maximum change in the time between pings being 10 seconds were accumulated to define a parking stop. The total time of these pings was defined as the dwell time for these events (Yang et al., 2014).

Dwell time is also calculated through spatial variables. Gingerich et al. (2016) used a tethered approach based on a buffer distance. The first GPS ping has a 250-metre buffer applied. Successive pings within that buffer are considered part of the stopping event once the dwell time exceeds 15 minutes. This process reduces false positives with slow-moving vehicles due to congestion but allows some variance in ping location caused by low-accuracy signals. The data used in this thesis is pre-processed using the above approach and will be discussed in detail in Chapter 3.2.1.

An observation is that multiple deliveries in the same location are correlated with larger individual dwell times. A study by Kim & Boyle (2021) observed commercial vehicles' dwell times based on various locations (freight-related and residential or other locations) in Seattle, Washington. The study compared personal vehicle deliveries to larger commercial vehicles and the size of the vehicle and found a positive correlation between larger vehicles and longer dwell time (Kim & Boyle, 2021). The same study also provides some strategies based on the observed parking trends of freight vehicles at these buildings. The most relevant strategy proposed is the implementation of context-specific commercial vehicle parking time limits. Kim and Boyle's analysis indicated that there were more parking-related infractions in one of the commercial buildings in the study compared to another. This building possesses constraints imposed such as the limited space within the property to make deliveries. Drivers may need to find external space where they face the possibility of being ticketed for unauthorized parking. The other commercial buildings within the study did not have strong limitations and as such had fewer infractions. The study's conclusion was that the status of the location based on access can affect the dwell time at locations where goods are exchanged (Kim & Boyle, 2021). This may be analogous to restrictions on distribution centres leading to longer dwell times and parking infractions on roadways and rest facilities within the Region.

A study by Kinjarapu et al. (2021) builds upon an entropy analysis from Gingerich et al. (2016) to understand correlations between dwell time and the entropy of parking locations. Entropy is defined as the variance of truck carriers at a location. Areas of high entropy based on truck carrier variety and frequency are considered secondary activity locations (e.g., resting or filling up gas). Trucks that represent a multitude of firms visit these locations. In terms of dwell time, these locations had an uneven distribution of dwell times with no discernable relationship between the frequency of trips and dwell time. Areas of low entropy are considered primary activities (e.g., shipping, receiving, etc.) and possess a negative exponential relationship in the frequency of dwell times. For these areas, the dwell times examined possess consistent values of low dwell time. In other words, areas with low entropy include freight activities with consistent dwell time values compared to high entropy areas with more inconsistent dwell time values (Kinjarapu et al., 2021).

2.4.2 GPS Data in Freight Applications

Obtained GPS trajectory data is used to identify groupings of truck parking (Yu et al., 2021). The authors applied GPS data to understand freight parking trends within Texas. Data analysis techniques, including machine learning techniques, were initially used to process the data. Once mapped, the researchers could determine areas of interest to propose improvements through added freight facilities. In particular, they analyzed specific stretches of interstate highways in Texas with elevated parking levels, indicating a lack of supply for parking nearby. The same authors identified parking location groups based on the frequency in which freight drivers frequent. Through this analysis, groups with short travel distances were noted of interest due to the potential of drivers looking for places to park rather than driving long distances and becoming stranded (Yu et al., 2021).

GPS data is used to estimate utilization or occupation at different facilities. However, the data represents a sample of observation rather than the entire population. Methods to factor these counts to estimate all truck parking activity are needed. Corro et al. (2019) analyzed two methods to factor GPS data to determine truck parking facilities using observational studies. A sample of GPS data is multiplied by these factors to estimate freight parking at facilities at a population level. The first factor is based on comparing observed GPS data to the overnight count of parking at parking facilities. The second factor is based on comparing observed GPS data to traffic on roadways adjacent to rest areas using weight in motion (WIM) stations. Expansion factors are computed based on the type of facility, such as comparing public and private facilities. After applying the overnight count factor and the traffic factor separately, the error between these expanded GPS counts to the observed count at the rest area facility is obtained. The mean absolute percent error for the overnight study ranged from 45-60% based on parking facility type. The roadway study saw 145-300% errors based on parking facility type. The error discrepancy was noted based on how the observed traffic varies between WIM stations examined in the roadway study (Corro et al., 2019).

Due to the above error, the expansion factors calculated in the study vary by a multiple of 12 depending on the site. After applying each type of factor to the study's parking facility location GPS counts, the overnight counts estimated parking capacity at 30 percent over capacity compared to the roadway counts estimating capacity at 49 percent over capacity. The contrast between these factors indicates that multiple expansion methods should be proposed and tested (Corro et al., 2019).

2.5 Optimization Techniques

The field of mathematical programming, known more commonly as mathematical optimization, provides a means to determine the most efficient use of resources given the constraints posed by a problem. In freight transportation, optimizations are used to solve problems to allocate resources for deliveries. An example problem is determining warehouse locations based on infrastructure and transportation costs. Sert et al. (2020) used optimization to determine additional locations for warehouses while providing cost reductions in transportation.

Problems that aim to determine the optimal location for facilities to service demand for a set number of demand points are location-allocation problems. Cooper presents a basic form of this problem as determining the number of origins, the location of each origin, and the capacity of each location based on the given location of each destination, the demand at each destination, and the cost of transport from origin to destination (Cooper, 1963). Optimization strategies are used to determine the solution to these problems.

One type of location-allocation problem is the added consideration of capacity or the cost of the facility. Another type of allocation problem is identifying the spatial extent to which facilities can provide service. Incrementing the number of open facilities to allocate demand is also a location-allocation problem. This thesis uses an optimization scheme to allocate distribution centres and rest areas. An application of each location-allocation problem is reviewed to provide context for the appropriate location-allocation problem that is considered for this thesis to be solved with optimization.

2.5.1 The Hitchcock Transportation Problem

Allocating destinations to a facility based on the demand at the destination is a common problem in supply chain research. The Hitchcock transportation problem describes this problem of minimizing costs between facilities and demand points. The cost typically represents a travel-based quantity, such as travel distance or travel time. In other words, the goal is to allocate demand to the closest facilities. The problem is further constrained by the supply of facilities meeting the demand (Sadeghi, 2018).

However, the supply that a facility can provide only needs to meet the demand. Therefore, this constraint is simplified as supply is equal to or greater than demand. Initially formulated by Hitchcock et al. developed the simplex method to solve the transportation problem as a linear programming problem (as cited in Sadeghi, 2018). In other words, this algorithm allows these problems to be computationally straightforward. This simple problem allows for the allocation of demand based on supply but does not consider further constraints such as the consideration of varying the number of facilities.

2.5.2 Capacitated Plant Problem

Facilities have costs that are determinants in the allocation of demand or the location of facilities. One type of cost is the fixed operational costs of a facility. Facilities also are constrained by the amount of supply, also known as capacity, and the variable costs required to facilitate each unit of cargo.

The capacitated plant location problem is a location-allocation problem that considers both of the above factors (Sridharan, 1995). In other words, this problem balances the variable cost of travel between demand points and facilities with the attempt to choose facilities with lower fixed costs. However, the fixed cost of a facility may not be easily defined or an exact quantity to use. This problem is not selected for the thesis since the costs of developing and maintaining a rest area in the Region of Peel are outside the scope of this study.

2.5.3 Maximal Service Area Problem

Facilities are characterized by the extent to which they can provide service. A service area is represented by a spatial zone in which a facility provides coverage. GIS provides tools to develop these areas as polygons based on a given travel impedance.

A modern application of a service area is the 15-minute city in which planning strategies implemented should result in access to necessities and amenities within 15 minutes of residential housing (Moreno, 2020 as cited in Pozoukidou et al., 2021). A service area is a solution to determine if an amenity is within 15 minutes from neighbourhoods.

The maximal service area problem is a location-allocation problem that determines the locations providing the maximum coverage area facilities can provide to demand nodes (Indriasari et al., 2008). In this thesis, the service areas for rest areas can be created to determine the number of distribution centres that fall within that area. However, the solution can provide context to the coverage of facilities but may not offer the optimal pairing due to overlap.

The solution algorithm also plays a role in the variance of results due to model complexity. Within Indriasari's study of fire stations in Jakarta, Indonesia, the use of algorithms like genetic algorithm, tabu search, and simulated annealing improved the coverage of the service areas of these stations from 74% of the city's area for the base algorithm to approximately 80 to 84% coverage (Indriasari et al., 2008).

2.5.4 P-median Problem

The P-median problem is a location-allocation problem that determines the optimal solution for allocating demand points to facilities based on the number of proposed open facilities. The optimization is done by minimizing the cost of the demand points and facilities. The P parameter represents the number of open facilities in the problem. One of the earliest considerations of this problem is presented in a study by Baumol and Wolfe in 1957 to consider the transportation problem by determining the minimization of cost when considering multiple counts of warehouses. The objective of this problem provided by Mladenovic et al. (2007) is as follows:

$$min \sum_i \sum_j d_{ij} x_{ij} \tag{1}$$

where d_{ij} represents the cost between the demand points i and facilities j, while x_{ij} represents if a particular facility is servicing a demand point. This formulation is subject to the following constraints:

$$\sum_j x_{ij} = 1, \forall i \tag{2}$$

$$x_{ij} \leqslant y_j, \forall i, j \tag{3}$$

$$\sum_j y_j = p \tag{4}$$

$$x_{ij}, y_j \in \{0,1\} \tag{5}$$

where y_j represents the opening of a given facility and p represents the total number of open facilities.

Equation 2 in the model stipulates that every demand point can travel to one facility. Equation 3 in the model specifies that a demand point can only travel to an open facility. Equation 4 in the model stipulates that the total number of facilities opened equals the P parameter or the suggested number of destination facilities to be opened in the problem. Equation 5 in the model stipulates that the facilities can only be opened and closed and travel to a facility is a binary choice. Unlike the previously stated problems, the P-median does not include cost and total supply. The costs to operate a rest area facility within the Region of Peel are not well defined and can vary from firm to firm. Efforts to determine freight parking supply have been undertaken through modelling methods such as Nevland et al. 2020, but these values are still estimated. The P-median problem as an application within this thesis is conducted based on the examination of travel from rest areas to distribution centres based on the opening of a select number of facilities.

Examples of the P-median problem are reviewed to examine the outputs and impact of the applications of this model. A study by Chen et al., (2023) uses the P-median problem as a location selection process for new truck parking within the Michuhol-gu district within Incheon, South Korea. Within this study, an algorithm is applied to determine candidate sites in the district. The algorithm is based on keeping a distance away from residential areas, having a certain size of developable land, a minimal topographical slope, and proximity to highway infrastructure. After the identification of three candidate facilities, the P-median model was applied to one or two open facilities considered with the existing facilities of logistics firms within Incheon. With one facility open, the candidate facility with the lowest average travel time is chosen. With two facilities opened, the two candidate facilities with the lowest average time times are chosen. This output presents an obvious solution when there is only one site selected since the facility providing the lowest total travel time is selected. It is expected that with larger values of the P parameter, there would be an increased complexity to consider. However, the output allocation for each number of open facilities presents the differences. When the number of open facilities changed from one to two, the firms within the southeastern corner of the district were allocated to the second facility with two open facilities. In other words, the P-median problem is used in this analysis to allocate firms to facilities by varying the number of facilities opened even when performance benefits are not obvious (Chen et al., 2023).

A study by Tadić et al. (2023) presents an application of the P-median problem to determine the best households to implement a collection and delivery points (CDPs) system in Belgrade, Serbia. The system of CDPs analyzed is based on the use of households as destinations for last-mile logistics that will act as hubs for final deliveries to households within the area. The P-median problem is used to vary the number of open CPDs within the city of Belgrade and to identify locations as CPDs and the improvements in travel distance for the final delivery. Within their analysis, they noted that for every ten CPDs that are open, the system sum of distances is reduced by 14.1% on average. The average length of trips for the final delivery reduces from 2.7 km with 30 CPDs to 1.6 km with 70 CPDs or a 40% reduction. They also identified that a total of 5140 CPDs are needed to achieve a minimum distance of 0.5 km (Tadić et al., 2023). This study presents the benefit of using the P-median model to quantify the benefits of incrementing the number of open facilities.

A study by Murat et al. (2021) aims to optimally choose public healthcare facilities based on the population density of districts in Jeddah, Saudi Arabia, based on the minimization of travel distance. Within their study, 36 health centres were identified within the 110 districts within Jeddah. The P-median problem was applied with the opening of all health centres within the city to determine the best healthcare facility to locate for each district with demand being the population density for a district. This analysis presented the significant gaps in access to healthcare for people who live within low-density areas due to the model assigning significant distances between these districts and nearby health facilities (Murad et al., 2021). Although this study is in a healthcare context, the results presented the ability of the problem to showcase certain areas that do not have ready access to facilities.

2.6 Chapter Summary

The Covid-19 pandemic has had a specific impact on society, and freight workers are particularly affected. Within the Region of Peel, truck drivers were noted to share a sizeable proportion of infections and contribute to the spread of the illness. These workers already face issues with access to space to provide parking, leading to problems with increased collisions due to increased fatigue from drivers. Hours of service regulation will further increase the demand for rest areas due to imposed rest periods for these drivers. Intermediate solutions can be implemented to increase supply, and existing parking within a jurisdiction can be categorized and identified.

To analyze freight parking, GPS data representing these events can be obtained. This data can be processed to determine the length of time that has elapsed for an event. This dwell time can provide context to the type of activity that occurs at firms, and relationships can be formed, such as the frequency of activity at a location. These relationships can also be utilized to determine factors that can be implemented in analysis.

The literature review highlights that truck drivers face issues when accessing rest areas. Distribution centres represent a major location in which trucks travel to exchange goods. Location allocation optimizations can be a tool to determine the ideal rest area locations to service eventual travel to distribution centres. The P-median problem, in which the number of open facilities can be differentiated and optimally locate each demand to an available facility. This problem provides the optimal facility for the firm but also identifies the facilities that provide the most utility when resources are limited. Applications of the P-median problem have been presented to showcase the benefits of the incrementation in the model, as well as the relevant performance metrics.

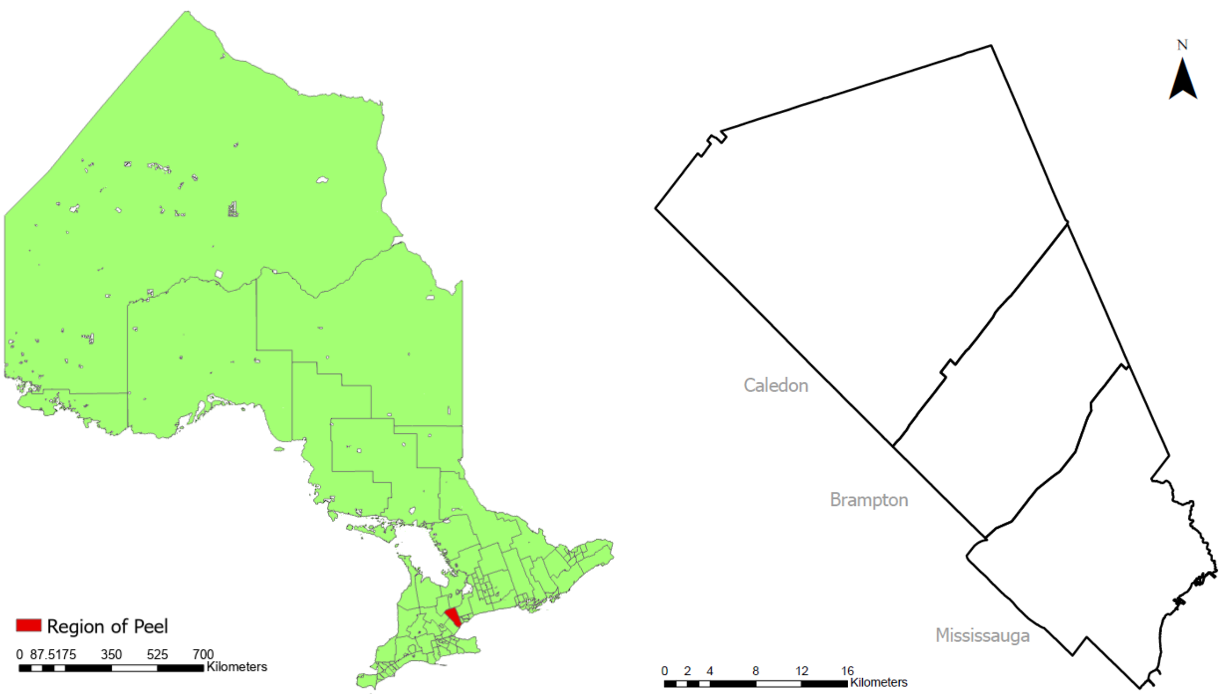
A similar approach is conducted in this thesis to allocate distribution centres to rest area facilities and subsequently identify important facilities amongst limited resources during a pandemic. The limited resources are tested by varying the P parameter or the number of facilities in the P-median problem.

CHAPTER 3: STUDY AREA AND DATA

3.1 Study Area

3.1.1 Region of Peel Municipalities

The Region of Peel is selected as the study area due to the high concentration of freight activity (see Chapter 1.2). Figure 1 shows the geographical scope, based on the boundary of three municipalities, including Mississauga, Brampton, and Caledon.



Region of Peel Location
(adapted from Land Information Ontario, 2023)

Region of Peel Municipalities
(adapted from Region of Peel, 2021b)

Figure 1 Three Municipalities in the Region of Peel

As a major freight hub, the road network of these municipalities has a sizeable amount of truck traffic on its roadways. Over 65,000 trucks per day were present on Region of Peel roadways in 2012 (Region of Peel, 2017). The Region of Peel has identified the critical roadways to the freight industry and designated these roadways to the Strategic Goods Movement Network (SGMN). Figure 2 below presents the Strategic Goods Movement Network.

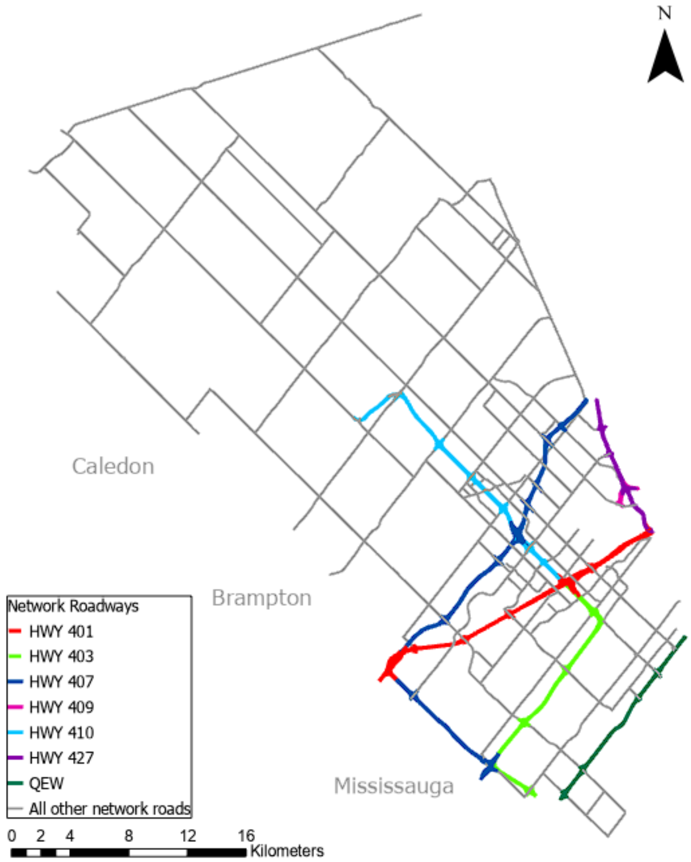


Figure 2 Strategic Goods Movement Network (adapted from Region of Peel, 2017)

The municipalities are divided into smaller areas. The Greater Golden Horseshoe Model (GGHM) developed by Ontario's Ministry of Transportation uses a set of areas based on shared transportation-related factors. The factors include population and employment counts and density, land use and transit use (Ministry of Transportation, 2011). These areas are also called traffic analysis zones (TAZ). The count per municipality includes Caledon with 42 zones, Brampton with 167 zones and Mississauga with 168. One zone for eastern Brampton is shared with the neighbouring municipality of Vaughan. Figure 3 below presents these TAZs for the Region of Peel.

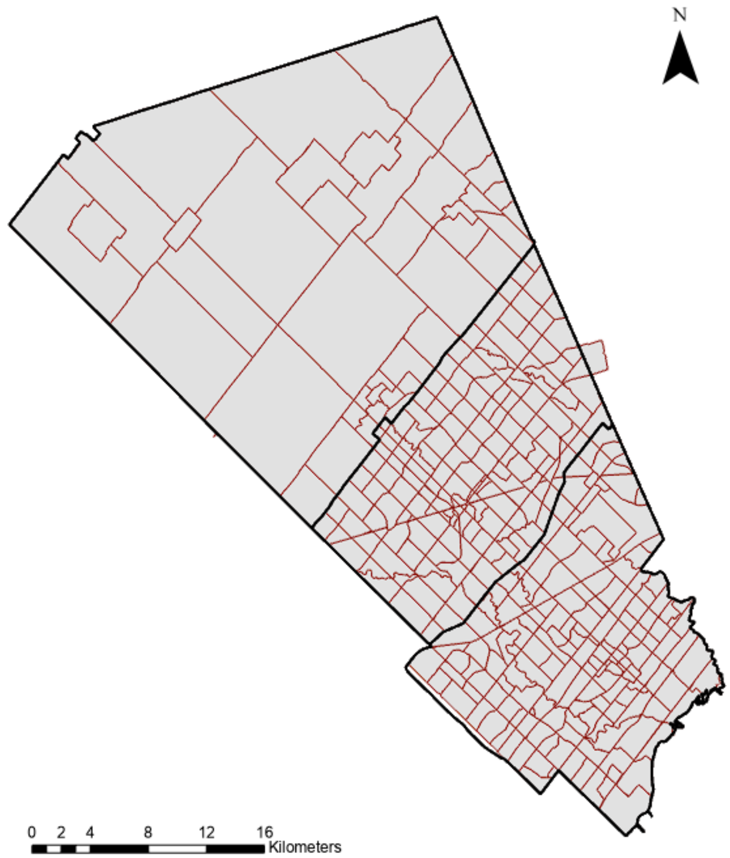


Figure 3 Traffic Analysis Zones (adapted from Ministry of Transportation, 2011)

3.1.2 Major Freight Locations

The Goods Movement Strategic Plan by the Region of Peel highlights important locations as major points of interest to ensure goods are moved efficiently, as shown in Figure 4. These points of interest include the 400 series highways in the Goods Movement Network in Figure 2. These freeways deliver a major portion of traffic within the region and are crucial to efficient freight flow. For example, in 2019, Highway 401 segments across Mississauga had an annual average daily traffic of approximately 200,000 vehicles (Ministry of Transportation, 2020). Toronto Pearson International Airport is also a major source of air cargo. As mentioned in Chapter 1.2, Pearson Airport has the most air cargo being transported in the country. The Canada National (CN) Intermodal Terminal in Brampton and the Canada Pacific (CP) Intermodal Terminal across the municipal border in Vaughan provide an exchange point between trucks and rail cargo. The CN terminal in Brampton handles 60% of all intermodal traffic for CN (Metrolinx (n.d.), as cited in Region of Peel, 2017).

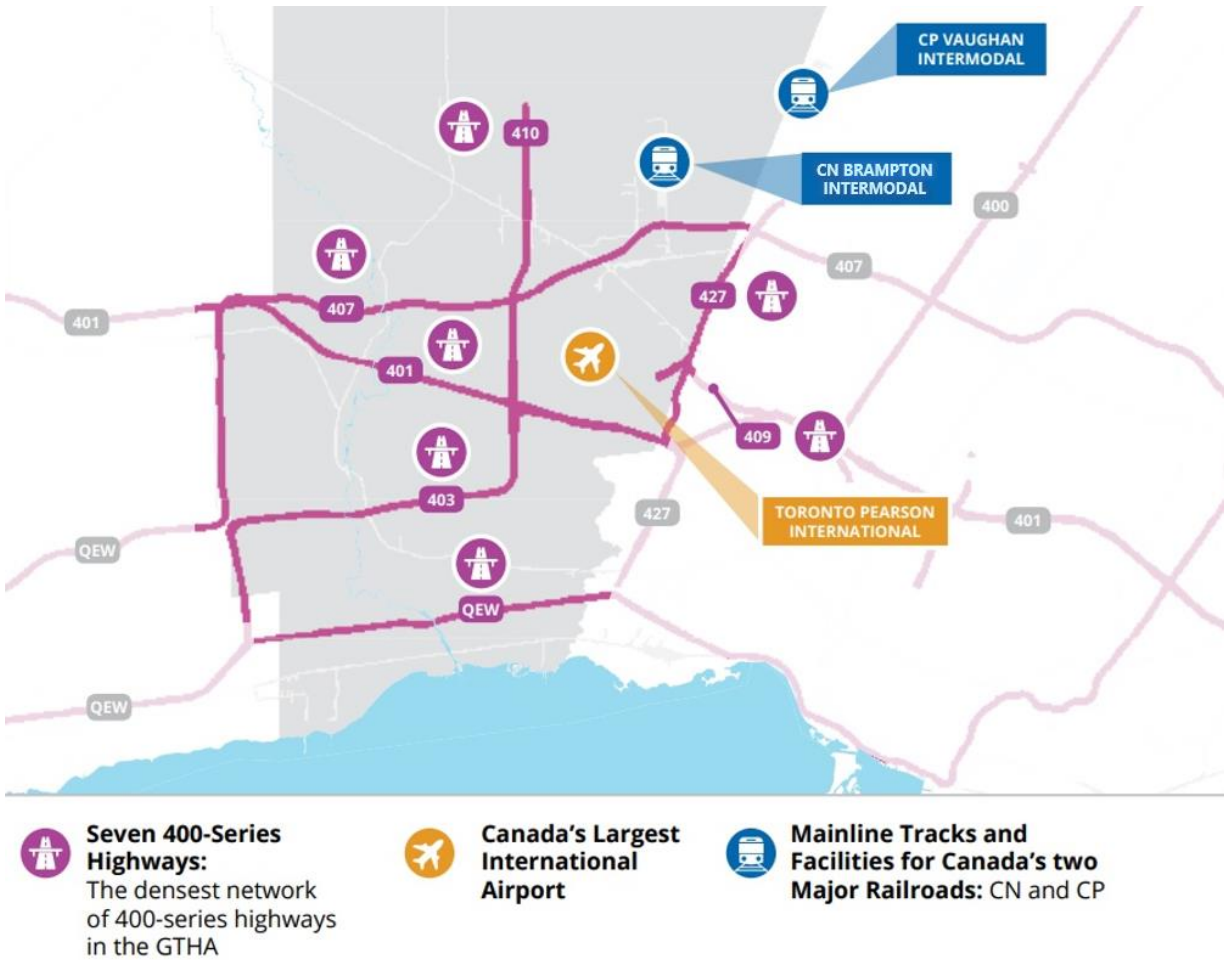


Figure 4 Major Points of Interest in the Region of Peel (adapted from Region of Peel, 2017)

3.2 Data Sources

3.2.1 GPS Data

The York University research team obtained ATRI GPS data from the University of Toronto (UofT) on January 21, 2020, through data partnerships in the Smart Freight Centre. Table 1 shows a summary of the processed data.

Table 1 GPS Data Summary

Description	2019	2020
Date acquired	Mar 15, 2021	Jan 21, 2021
Time Frame	Jan 1, 2019 to Dec 31, 2019	Feb 1, 2020 to Jul 31, 2020
Study Period	Feb 1, 2019 to Jul 31, 2019	Feb 1, 2020 to Jul 31, 2020
Number of trucks	19,004	88,370
Number of stops	577,609	1,105,744

The dataset is pre-processed from GPS pings of truck parking activity used to create processed stops. This pre-processing was completed by Dr. Kevin Gingerich of York University. The speed data field was not provided with the raw GPS data; therefore, the dwell time is calculated based on recurring GPS pings within a given area representing approximately 250 metres, as previously performed by Gingerich et al. (2016).

The pre-processing is completed using Microsoft SQL Server 2019 version. The initial processing steps included the following:

1. Inputting initial data,
2. Sorting data records by truck and date/time,
3. Creating a unique identifier for each data record,
4. Calculating elapsed time between pings,
5. Calculating dwell time for stopped vehicles,
6. Identifying stop events with dwell times greater than 15 minutes, and
7. Creating indexes to speed up future data queries.

This processing performed by Dr. Gingerich was completed on February 11, 2021. Two issues were identified after the first round of data processing. These included 1) false positive parking events, and 2) inaccurate locations after a truck has completed a stop. Specific locations of these issues were identified and resolved by the York University research team.

The false positive parking incidents were identified primarily from highway locations where stops are infeasible, such as a main segment of Highway 401. These events shared a common attribute with only two pings (first and last) associated with the false stop. Often, it was found that these events resulted from a vehicle leaving the study area (Region of Peel) and then re-entering the area later on the same road corridor. Follow-up processing was subsequently conducted to remove stops containing only two pings. This procedure resulted in 5 percent (69,151) of the stops being removed from the 2020 dataset, with 1,237,992 stops remaining. The remaining stops were filtered out by establishing a 24-hour maximum on these stops to obtain the number of stops present within Table 1. In the future, speed data given with the ATRI GPS pings is expected to enhance this process by removing events where the vehicle is found to be in motion.

The second issue pertained to inaccurate locations of the stop events, often displayed on a local roadway near the distribution centre where a stop occurred. This problem resulted from associating the location for each stop based on the final ping for the event, often as the vehicle started moving again. This issue was mitigated by averaging the location of all pings associated with a given stop. Speed information could also be used here in the future to remove pings where the vehicle is found to be in motion.

The received dataset of truck stops was provided in .csv files with each data record containing a truck ID, date, time, latitude, and longitude. The date and time of each stop are presented at the beginning of the event and the end of the event. Therefore, the dwell time is computed as the difference between the time stamps for each stop. The minimum dwell time based on the pre-processing is 15 minutes. Within 2019, the data includes 19,004 unique trucks based on the truck ID, though the actual number may be smaller if a single vehicle has the ID occasionally changed. Within 2020, there are 88,370 unique trucks due to the inclusion of a new group of Canadian trucks added to the primarily American ATRI dataset for this year increasing the number of trucks considered. Both counts of trucks for each study year are based on the study period months of February to July of each year. For 2019, the received data ranges from January 1, 2019 to December 31, 2019 but the study period ranges from February 1, 2019 to July 31, 2019. For 2020, the data received and used for this study ranges from February 1, 2020 to July 31, 2020.

3.2.2 Distribution Centres

Many distribution centres (DCs) are located in the Region of Peel with varying levels of trip productions and attractions. This section explains the strategies used in this study to identify DCs. Initially, a list of potential DCs is compiled in Figure 5 based on the following three major sources of information:

1. The McMaster Institute of Transportation & Logistics (MITL) report was published in 2014 (Ferguson et al., 2014). The report contains a list of firms that attract or generate significant freight activity in the Greater Toronto-Hamilton Area.
2. The DMTI Enhanced Points of Interest (DMTI, 2020). These points represent a nationwide dataset containing areas of interest filtered by Standard Industrial Classification (SIC) codes. Locations with Code # 4225 for warehouses are screened.
3. The ATRI data. The York University research team used the plotted GPS data to screen areas with intensive parking activities. Google Maps is used to identify the company associated with the MDC manually.

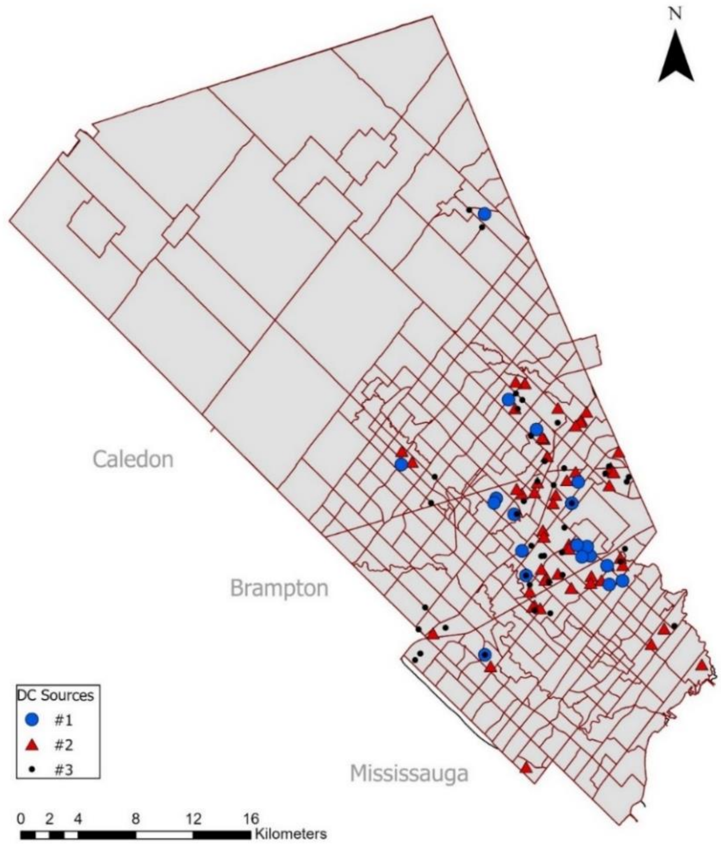


Figure 5 Distribution Centres Locations

3.2.3 Rest Areas

Rest areas are present throughout the region that provide parking for trucks. This section explains the strategies used in this study to identify rest areas for further consideration. Initially, a list of potential rest areas is compiled in Figure 6 based on the following three major sources of information:

1. A dataset from Nevland et al. (2020) identified rest areas within the Region of Peel.
2. The DMTI Enhanced Points of Interest (DMTI, 2020) Locations with Code # 5541 for gas stations are screened. Of the 260 firms within the region assigned that code, only three represented firms with dedicated truck parking.
3. Based on the above two sources, identifiable firm names associated with truck parking are found. These firms include Petro-Pass Truck Stop, Husky Travel Centre, and Flying J Travel Centre. Additional Petro-Pass Truck Stops are found in the

region not covered in the previous two sources presented in source 3. There is only one Flying J Travel Centre present within the Region of Peel, previously identified in Source 1.

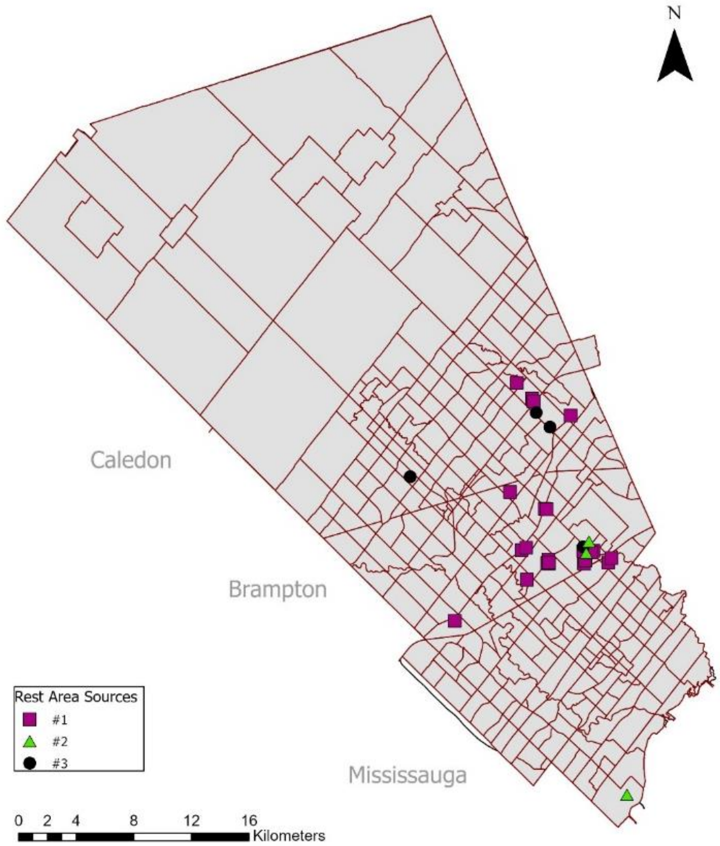


Figure 6 Rest Areas Locations

3.2.4 Parking Restriction Bylaws

The Region of Peel's parking bylaw information is used to identify roadside locations where are allowed to park. The bylaws set by each municipality include the City of Mississauga's No Parking Bylaw (2020), the City of Brampton's No Parking Bylaw (2020), and the Town of Caledon's No Parking Bylaw (2019). This study focuses on parking activities on major/minor arterials or collectors near MDCs. The data processing did not include local roadway parking and restrictions in residential areas since the MDCs are located in commercial or industrial areas.

A shapefile using ArcGIS is created to visualize the parking restrictions over space. Several fields (i.e., input variables) are recorded for each side of the screened roadways, such as parking restrictions' start and end times, applicable days, or applicable months. Figure 7 displays the non-residential streets that have freight parking restrictions within the Region. This figure was generated was developed by the York University research team as part of a contribution to a Transport Canada project conducted in 2021 (Park et al., 2021). Most parking restrictions are observed in Mississauga. The parking restrictions in Brampton mainly occur along the arterials, while Caledon shows non-residential parking restrictions in a limited industrial area in southeastern Caledon.

Using the GPS data provided by ATRI, the intensity of events occurring on these restricted roadways is presented in Figure 8 below. Based on Figure 8, some key areas are noted as possessing higher intensity on roadways with restricted parking. The increased level of parking in restricted roadways presents a need for rest area facilities. Prioritizing existing resources provides an opportunity to reduce the need for this parking.

Figure 7 Truck Parking Restriction on Non-Residential Roadways

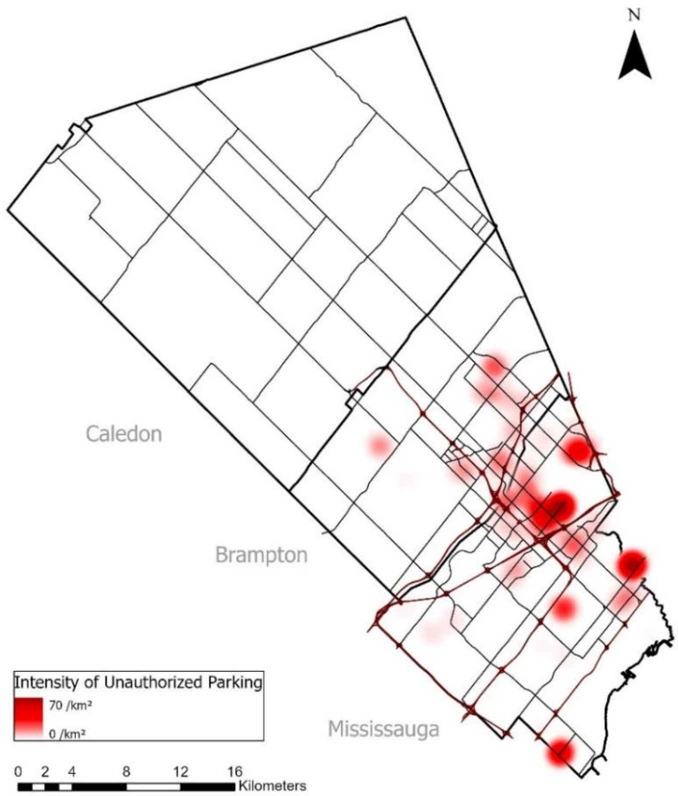


Figure 8 Intensity of Truck Parking in Restricted Roadways - 2020

3.3 Chapter Summary

The Region of Peel represents a major freight area in Canada. The Region is made of the two cities of Mississauga and Brampton and the town of Caledon. Within the region, seven major freeways and other major arterials comprise a road network identified for heavy freight use. In addition, an intermodal terminal within Brampton represents a major point of exchange of goods between land and rail freight. Pearson Airport also represents a hub for air cargo. The Greater Golden Horseshoe model also provides traffic analysis zones that break apart the region into zones that possess similar transportation characteristics.

GPS data is obtained to analyze truck parking activity in the Region of Peel. The data is representative of February to July of 2019 as the pre-pandemic year. This is due to the availability of GPS data from February of July 2020 representing the pandemic year. This GPS data was further processed similarly to Gingerich et al., 2016 to determine parking stops. compared to Approximately

580,000 stops are processed for 2019 compared to approximately 1.1 million parking stops are processed in 2020.

An initial list of distribution centres is identified through a review of available sources. These facilities are identified from many sources, including existing literature, readily available datasets, and a manual searching approach. A similar exercise produces an initial list of rest area facilities. An initial data exercise is also conducted to use parking restriction bylaws and the processed stops obtained to determine the intensity of parking in restricted roadways. The output of this analysis highlights the need for rest area facilities. This need is addressed through the prioritization of existing facilities. The next chapter will present the methods of analysis to determine these solutions.

CHAPTER 4: METHODS OF ANALYSIS

The following methods outline the processes conducted within this study. Firstly, data processing is examined in Section 3.2.1 GPS Data. The temporal dimension of the data is discussed to determine the patterns of freight parking between the pre-pandemic and pandemic years. These processes are employed to identify parcels with a large amount of parking activity, classifying them as major distribution centres (MDCs). An algorithm is then developed to determine overnight parking in the region and to identify the major rest areas (MRAs) for further analysis. Overnight parking is an important component of long-haul truck driving due to documented issues related to fatigue and the limited availability of rest areas (Crizzle et al., 2020).

A gravity model is used to determine factors affecting travel time for trips from rest areas to distribution centres. The model facilities the determination of the exponential relationship between travel time from rest areas to MDCs and the demand for travel for these specific trips. The exponential relationship is observed due to the non-linear relationship between travel demand and travel time as a cost. Using the observed overnight trips, the model is derived to obtain cost factors considered in the optimization as a non-linear influence. To conduct this optimization, the P-median problem is presented with an adaptation tailored to this study. The P-median problem aids in determining solutions to the resource allocation of rest areas under limited resource conditions. Identified overnight trips will be optimized based on travel demand to distribution centres and the exponential cost of travel. The outcome of this process is to identify the key facilities that should be prioritized during pandemic conditions.

4.1 Processing GPS Pings

The data in Chapter 3.2.1 is processed to sort each ping by truck ID and date/time such that each point is organized in consecutive order. Subsequently, consecutive GPS pings within a fixed 250 m radius are identified and a dwell time within the radius is established. This method is discussed in more detail by Gingerich et al. (2016). A speed variable is not provided with the raw data, making it unsuitable for generating dwell times or stops. Speed can be inferred from the data points but is sensitive to errors caused by 'signal jiggle' resulting from too few satellites or urban canyons.

A dwell time of 15 minutes to 24 hours is used to identify stops pertaining to trips. A dwell time of fewer than 15 minutes is not typically associated with rest breaks or MDC deliveries within the scope of this study which sets the minimum value considered within the pre-processing. Dwell times exceeding 24 hours are also outside the scope since these long stops are not expected in the middle of a trip associated with a rest stop; they are more likely to represent the end of a trip. Applying the 15-minute to 24-hour filter resulted in 1,105,744 stops in 2020 and 577,609 stops in 2019.

Data points that create false positives due to entry coupled with re-entry within and outside the study area, particularly on the freeways, are identified and removed. Another issue identified is duplicate stopping pings creating inaccurate locations within facilities that are aggregated. More information regarding these additional processing steps is found in Chapter 3.2.1.

The data is presented as stop events in date format for two dates indicating the time of entry and exit. The difference between these two date variables represents the dwell time the trucks park at a location. A corresponding day of the week and the hour of the day are associated with each date. Since the data ranges from 15 minutes to 24 hours, certain stops may span two days such as both Monday and Tuesday. Binary variables are therefore set up for every hour over two days for a total of 48 hours considered. A variable is set for every hour from 12 a.m. to 11 p.m. on both days considered. As binary variables, the data is presented as either a true value of 1 or a false value of 0 depending on the condition that a rest event is occurring on that specific hour.

For example, if an event ranges from 10:30 p.m. on Monday to 5:45 a.m. on Tuesday, then the value for binary variables for each hour will be 1 for the hour variables starting with the 10 p.m. to 11 p.m. time slot on Monday and the 12 a.m. to 5 a.m. time slot on the following day for a total of 8 hours with a true value. All other hourly variables outside the range in this example are represented with a false value of 0. It is worth noting that the hours are not rounded and hence an event at the 59th minute will not be considered as occurring for the next hour.

4.2 Analysis of Stop Events

The stop events generated from GPS data are further processed in ArcGIS Pro for spatial analysis filtered for various conditions. These conditions include the length of the parking event, the time of day, and the day of the week. The duration of the parking event is of interest due to the assumed behaviour of events that are short compared to long-term events. For example, short events are expected to be located in MDCs where an exchange of goods is expected, as noted by Crizzle et al. (2020), compared to longer durations occurring at rest areas. The time of day is important when comparing trends for events. The morning represents the immediate period after the overnight, indicating trends from trips associated with rest areas. The afternoon is also of interest due to trips involving an increased mix of vehicles outside of freight during peak hours. Finally, the day of the week is of particular interest due to the comparison of behaviour on weekdays to weekends when certain businesses are not in operation.

Two main types of analyses are conducted using ArcGIS Pro including kernel density analyses to identify hot spots for stop events per unit area, and spatial join analyses to identify the frequency of stop events by traffic analysis zone (TAZ). Since the GPS datasets for 2019 and 2020 have different sample sizes, proportions of the data are often provided in this study to facilitate a better comparison between the two years.

The spatial join analyses are carried out by joining the stop events with TAZs identified. The spatial differences between the two years help determine where the parking pattern shifted during the onset of the pandemic. The TAZs are used for this analysis based on the common transportation characteristics in the area. However, note that these zones were constructed for the 2011 model and hence may be outdated in their representation. They were initially created with transportation planning in the Greater Toronto and Hamilton Area as a major consideration and remain a valid representation of zones for this thesis.

The spatial join is next used to merge the stop events with parcels provided by the Region of Peel that provide land use designations to determine the impact of the pandemic on the types of land use. Land uses designated in the region include Industrial, Commercial Services (COMMSVCS), Airport, Office, Institution, Green Space, Vacant, Low-Density Residential (RESLOW), Medium Density Residential (RESMED), High-Density Residential (RESHIGH), Agriculture, Government (GOVT) and Right of Way (ROW). An additional land use called INDUSTEXTR (Industrial Extraction) is also examined, encompassing select parcels with industrial pits and/or quarries within the site.

Brampton is the only municipality within the region that does not possess an Airport land use, while the other two municipalities possess all uses. However, it is to be noted that the airport within Caledon is a privately owned facility used for training and recreation with limited freight activity (Brampton Flight Centre, 2023). After the join, the proportion of the data per use is presented in graphical format. Specific land uses of interest include commercial, industrial, office, and residential areas. Commercial and industrial areas are the typical locations where freight parking is expected, but due to the pandemic, remote working practices have emerged, which may affect freight activity in office areas. Residential areas are also of interest due to potential issues in freight parking supply leading to unauthorized parking in these neighbourhoods.

The stop events are spatially joined to more finite parcels provided by Teranet to determine parking activity at the firm level. Teranet is a firm that provides land & commercial registries for the Province of Ontario and developed the Ontario Parcel database which is used as a shapefile for parcels. This data is used to identify the top 50 MDCs based on parking activity. The MDCs are represented by their TAZs for each year and compared between the municipalities. The top 50 MDCs are selected due to limited parking activity from the remaining distribution centres. The locations of the MDC firms are displayed by zone in later results to preserve anonymity.

The MDCs are presented with temporal conditions based on a series of filters. The first analysis involves comparing the length of the parking event, with a benchmark of two hours used to segment the data into two categories: events of two hours or less and events lasting more than two hours. The next analysis examines when parking events end and the truck proceeds to travel to its next destination. The periods of travel of interest are typical peak hours shared with automobiles, which include the A.M. peak from 6 a.m. to 9 a.m. and the P.M. peak from 4 p.m. to 7 p.m. To obtain these events, the end time of parking as a truck begins its trip must be 6, 7, or 8 a.m. for the morning or 4, 5, or 6 p.m. for the afternoon. Another analysis is conducted based on the day of the week. Thursday emerges as the most common day, while Sunday is the least common, leading to a further comparison between weekdays and the weekend.

After determining the top 50 MDCs, the locations of parking events before arriving at these distribution centres are observed. In particular, areas with large amounts of overnight parking activity are of particular interest due to issues regarding nighttime access. To identify these events, the following criteria are used: the preceding event cannot be at another MDC, the event must be at least 120 minutes within an overnight period between 9 pm to 6 am., and the time between the preceding event and the event observed in an MDC is half a day or less. The first criterion is considered since the focus of this analysis is to determine areas of freight parking to identify MRAs. Parking within MDCs in the overnight period is out of scope since these drivers would be associated with the firm they are residing in. An assumption is made that if a driver can park within an MDC overnight then they would not need to use a rest area facility. The next two criteria are considered to ensure that the stop is representative within an overnight period. The last criterion is used to ensure that the trip to the MDC does not occur after an extended period of time of the overnight stop. If the gap between the overnight stop and the eventual trip to an MDC is too long, then these two events are considered disconnected. After identifying these trips, a spatial join between the overnight trips and Teranet parcels determines the firms with overnight parking activity that go to MDCs the next day. A benchmark of 50 parking events is used to determine if these rest areas are significant enough to be included in further analysis. These facilities are the major rest areas facilities (MRAs) that are considered for this thesis.

The flow of traffic between two points is varied based on the spatial interactions of the two locations (Griffith & Fischer, 2013). The impedance can describe these spatial interactions defined by the cost of travel. One of these costs includes the travel time between the two locations and is typically used in accessibility studies (Phibbs et al., 2016 & Rad et al., 2021). The gravity model in transportation represents a method to generate trips based on the premise that a lower cost will increase the number of trips generated. This model is either constrained through the productions represented here as rest area demand or the attractions represented as the demand for travel to MDCs. Due to the pandemic-related restrictions imposed on MDCs, this analysis uses attraction-constrained modelling adapted from Equation 17 of Griffith & Fischer (2013) to determine a factor to apply to the travel time in optimization. The factors for travel time are obtained through negative binomial regression with the known values of origin and destination and provided travel time (Griffith & Fischer, 2013). Equation 6 below presents this adapted version:

$$T_{ij} = B_j O_i D_j \exp\left(-\theta t_{ij}\right) \tag{6}$$

where T_{ij} are the number of trips determined between rest areas and distribution centres, B_j represents the balancing factor for the destination, O_i represents the number of trips travelling from each rest area, D_j represents the number of trips arriving at each distribution centre, θ is the factor of time considered in the model, t_{ij} are travel times between each distribution centre and rest area.

The B_j parameter in Equation 6 can be rewritten as the denominator shown below in Equation 7. An α parameter is also added to the O_i to provide a calibration for the impact of size on the distributions.

$$T_{ij} = D_j \frac{O_i^{\alpha} \exp\left(-\theta t_{ij}\right)}{\sum_i O_i^{\alpha} \exp\left(-\theta t_{ij}\right)} \tag{7}$$

The singly constrained attraction gravity model is often used to determine the distribution of trips arriving at a set of destinations. Using the GPS sample of trips provides an opportunity to calibrate the model for trips travelling from MRAs to MDCs. Two parameters including θ and α are calibrated; however, only θ is needed for the optimization. The θ parameter is used to weight the impact of travel time in the optimization based on the observed distribution pattern. B_j, which includes the calibrated parameter α, is used as a balancing factor to balance total volumes between D_j and O_i in the singly constrained attraction gravity model and is not needed in the P-median optimization. The O_i variable is also not needed in the optimization presented in Equation 8 below since the traffic flow in the objective function is presented by $D_j x_{ij}$.

4.3 Optimization Formulation

In this study, a P-median formulation approach is used for the location-allocation of facilities. The problem aims to minimize the cost of travel within the network by selecting a group of facilities to supply the demand for another group of facilities. The "P" parameter in the name refers to the number of available open facilities selected to satisfy demand. For this study, the production facilities represent the major rest area (MRA) sites that provide nearby access to distribution centres.

The P-median problem is selected for this study due to the ability of the model to allow for a sensitivity analysis when considering the incrementation of the opening of facilities. For example, when the P parameter is set to 1, a network based on limited resources can be considered. Alternatively, when the P parameter is set to the maximum number of facilities, the ideal baseline network can be considered when the number of facilities is effectively left unconstrained. Incrementing the P parameter between these two values can be used to determine the incremental benefits of opening additional facilities. Relevant applications of this problem can be found in Chapter 2.5.4. The formulation of this problem also assumes that all trips to the destination are supplied by the closest facility. This simplification is well suited for this analysis since the capacity of the MRA is not considered due to the data limitations.

Overnight trips in the GPS data from rest areas to MDCs represent the demand. Overnight trips included in this process include trips for MRAs as well as parking areas that include gas stations, truck rental shops, and truck repair shops with at least ten parking stops. The demand for travel from MRAs to each MDC is weighted based on the negative exponential travel time, as denoted in Equation 6, to an assigned distribution centre, resulting in an objective function that minimizes travel costs. The nearest available MRA is therefore selected in the optimization to minimize cost. The availability of a given location changes based on the number of MRAs set by the P parameter.

The objective function for the P-median problem in this study is based on the formulation from Mladenovic et al. (2007). The original formulation in Chapter 2.5.4 has a value of cost that is not explicitly defined but common costs include the travel distance and travel time. In this thesis, the factorized travel time is considered the cost. The demand for travel to each distribution centre provides a weight to the cost, prioritizing MDCs with higher demand. Equation 8 below presents the formulation:

$$min \sum_i \sum_j D_j x_{ij} \exp\left(-\theta t_{ij}\right) \tag{8}$$

where t_{ij} is the travel time from MRA i to MDC j, x_{ij} represents if trips to distribution centre j originate from rest area i, D_j is the number of trips to distribution centre j, and θ is a coefficient to weigh the travel time based on a negative exponential function.

The term $D_j x_{ij}$ represents the traffic flow between the MRAs to the MDCs while the $\exp(-\theta t_{ij})$ term represents the factorized traffic time as a cost. The term $D_j x_{ij}$ is the flow due to the constraint presented in Equation 9 below such that all trips arriving at a destination MDC originate from one MRA. The product of the traffic and the cost of travel time represents the total system travel time which is the objective function minimized. The minimization of total system travel time provides a utilitarian approach. The D_j term represents the demand generated by the MDCs which implies that the MDCs with the highest demand will be prioritized for reductions in travel time over MDCs with limited demand. The output of increasing the P parameter will present the benefit of allocating the trips to MDCs to more facilities which may in turn reduce the spread of illnesses.

The formulation in Equation 8 is subject to the following constraints:

$$\sum_i x_{ij} = 1, \forall j \tag{9}$$

$$x_{ij} \leqslant y_i, \forall i, j \tag{10}$$

$$\sum_i y_i = p \tag{11}$$

$$x_{ij}, y_i \in \{0,1\}, \forall i, j \tag{12}$$

where y_i represents if rest area i is open or not and p represents the total number of open MRAs. The constraints are closely aligned with Mladenovic et al. (2007) 's original formulation. The y_i variable replaces y_j from the original since this analysis is based on P affecting the origin instead of the destination.

The constraint for Equation 9 stipulates that each distribution centre has trips originating from only one rest area. In other words, all trips heading to a specific distribution centre utilize the nearest available rest stop. Through this constraint, the closest rest area for every distribution centre for each P parameter is obtained. The Equation 10 constraint stipulates that a distribution centre can only have trips originating from an open rest area. This ensures that the selected subset of available rest areas is used and prevents trips from utilizing rest areas that are closed or not available. The constraint is crucial for low values of the P parameter since there is a minimal amount of rest areas open. The Equation 11 constraint stipulates that the number of open rest areas is equal to the predefined P parameter. The constraint for Equation 12 stipulates that the decision variables within the model output are binary. The binary constraints ensure that the model output presents the rest areas as open $(y_i = 1)$ or closed $(y_i = 0)$ and the travel from a specific rest area to a specific distribution centre as occurring $(x_{ij} = 1)$ or not occurring $(x_{ij} = 0)$.

To conduct the analysis, OpenSolver (Mason, 2020) is used as an open-source Excel add-in to set up the model within Microsoft Excel. The COIN-OR Branch and Cut solver is the chosen optimization engine, known for efficient computing solutions for linear problems (Forrest et al., 2023).

4.4 Model Alternatives

The P-median model is used to conduct the optimization of travel from MRAs to MDCs. The constraints for this model are suitable for this analysis due to the data limitations since capacity is not considered. If the dataset is expanded to represent the population, the specific counts of overnight trips at an MRA can be considered in context with its capacity. A version of the P-median problem with capacity constraints is discussed in this section to better understand the limitation of the previous formulation; however, the implementation of this section is beyond the scope of the thesis and is not included in the thesis results.

A capacity-constrained P-median problem is given in Equation 13 below based on a formulation presented by Yang et al. (2021) and adapted to this analysis based on Equation 8 above:

$$min \sum_i \sum_j x_{ij} \exp(-\theta t_{ij}) \tag{13}$$

This formulation is subject to the following constraints:

$$\sum_i x_{ij} = D_j, \ \forall j \tag{14}$$

$$\sum_j x_{ij} \leqslant c_i y_i, \forall i \tag{15}$$

$$\sum_i \ y_i = p \tag{16}$$

$$x_{ij} \geq 0, \forall i, j \tag{17}$$

$$x_{ij} \in \mathbb{Z}, \forall i, j \tag{18}$$

$$y_i \in \{0,1\}, \forall i, j \tag{19}$$

Where θ, t_{ij}, D_j, y_i, and p are identical to the previous P-median formulation. The parameter c_i is a new parameter representing the capacity of the rest area. The parameter x_{ij} now refers to the trip volume allocated from origin *i* to destination *j*. This differs from the previous P-median formulation when all trips to an MDC destination were assigned to the nearest MRA origin and therefore represented by 1 if true or 0 if false.

The objective function is based on the minimization of total system travel time, but the flow is represented by just x_{ij} since this decision variable is now representing portions of the demand towards an MDC *j* originating from MRA *i*. As such, the constraint presented in Equation 14 ensures that the total demand for travel towards an MDC is captured in the model. The constraint presented in Equation 15 ensures that the total number of trips originating from an open MRA is less than or equal to the capacity of the MRA. In other words, the constraint ensures that the MRAs that are chosen to be opened in the model output are not over capacity. Equation 16 is the same as Equation 11 and ensures that the total number of open MRAs is equal to a preset value of the P parameter. The constraint in Equation 17 constrains the flow into positive values since the model may mathematically consider negative values of flow to satisfy both constraints presented in Equations 14 and 15 that should be prevented. Equation 18 ensures that the flow is mathematically considered as integer values since a partial trip cannot be considered. Finally, Equation 19 represents the same constraint as Equation 12 and stipulates that an MRA can be considered open or closed as a binary choice.

The constraint presented in Equation 9 of the P-median model used later in Chapter 6 requires that all trips going to an MDC are provided by one MRA. However, this constraint presents the assumption that each facility has the capacity to handle all trips. In other words, with all trips assigned to a limited number of facilities, an increase in exposure to the virus is expected for the drivers interacting in crowded MRAs. A reduction in exposure in considered by increasing the number of MRAs opened at large values of the P parameter which reduces the number of trips originating at each MRA.

However, the P-median problem can be considered through a perspective of direct exposure to the virus. Equation 20 below presents an objective function that minimizes contacts:

$$min \sum_i \sum_j x_{ij} N_i^{close} \tag{20}$$

where N_i^{close} represents a parameter of close contact or person-to-person interaction between truck drivers at a rest area *i*. This parameter is based on a similar count of close contacts within a classroom presented in a disease-spread optimization study by Bagger et al. (2022). This parameter may simply be the expected number of contacts that a truck driver would encounter at a single stop at an MRA. The number of contacts can be estimated by a survey approach with truck drivers or through modelling based on the size of the facility. However, the parameter can be expanded by dynamic factors based on the epidemiological profile of the MRA. For example, if an MRA possessed a recent outbreak of a virus, then the parameter should be weighted higher since each contact is at a higher probability of carrying the virus. Another weight to consider is the epidemiological profile of the surrounding area. For example, higher weights can be applied to an area that an MRA resides in possessing an increased count of cases. The weights can therefore be dynamic based on the changing conditions of the pandemic.

The objective function within Equation 20 is based on the minimization of contacts between truck drivers at MRAs. An updated capacity-constrained P-median model for exposure can be considered by replacing Equation 15 with N_i^{max} presented in Equation 21 below:

$$\sum_j x_{ij} \leqslant N_i^{max} y_i, \ \forall i \tag{21}$$

where N_i^{max} is the maximum allowable trucks at an MRA or the maximum allowable value for the parameter. This value can be considered based on public health and epidemiological considerations of how many total interactions should be permissible at a given facility.

The t_{ij} travel times considered in this analysis are based on congested travel times generated by the most common trip times leaving the MRA when considering the trips from the overnight analysis. The most common time is 7 a.m. on Wednesday for 2019 and 6 a.m. on Thursday for 2020. Based on these starting times, the travel times between MRAs and MDCs are generated through the Network Analyst O-D Matrix within ArcGIS. However, this generation is conducted based on a network reflective of February 2022 which may not reflect travel times between facilities in the two study years. In particular, at the onset of the pandemic that is covered in the 2020 study year, traffic volumes were reduced compared to typical congested conditions (Stone, 2020). In this case, an alternative set of travel times can be generated based on an assumption of free flow or varying levels of congestion.

The P-median problem utilized in this study is small in size due to the count of facilities with 5 MRAs in 2019 and 8 MRAs in 2020. However, the problem can be expanded by increasing the number of MRAs and MDCs or considering a larger study area. The P-median model is an NP-hard problem that is computationally difficult to solve when considering large-sized models (Mu & Tong, 2020). Large P-median problems can be simplified by solving sub-P-median components individually. Mu & Tong (2020) proposed an algorithm based on two components: random sampling and spatial voting. First, random sampling is used to generate multiple smaller P-median problems based on a random selection of sites considered that will be optimized. Spatial voting is then introduced by generating a voting score based on the most common sites selected by the multiple models with sites added based on close proximity to the selected locations. The sites with the highest scores are then considered for a final P-median solution.

4.5 Optimization Scenarios

Within the optimization process, three scenarios are considered.

Scenario A: In this scenario, a set of MRA parcel sites defined by a minimum of 50 parking stops are identified using GPS data for each year. The P parameter is adjusted in this scenario from one to the maximum number of identified rest areas. Through the overnight trip analysis, five rest areas in 2019 and eight rest areas in 2020 represent the maximum value of P for this scenario. With the maximum number of MRAs opened, the baseline network is presented since the MDCs will have their trips originate from the closest MRA to each of their locations.

Scenario B: This scenario expands the potential locations for rest areas across a larger area by using zones covering the Region of Peel instead of individual parcel sites. The TAZs from the Greater Golden

Horseshoe Model for Mississauga and Brampton are used for this study. Figure 3 presents the TAZs but only Mississauga and Brampton zones are used for this analysis. The Town of Caledon has a fewer number of TAZs since it has a smaller population. Instead, the Dissemination Areas are used for the Town to provide more zones and potential locations. These zones are obtained from the Region of Peel Data Centre and form part of a nationwide zone system for census information (Region of Peel, 2021b). The zones can be viewed in later resulting maps such as Figure 26. The total number of TAZs used for Mississauga and Brampton is 335 and Caledon possesses 91 Dissemination Areas for a total of 426 zones. The centroid of these zones represents the specific location within the zone where the rest area is to be located. The P parameter included individual results for 2, 6, and 10 selected zones. The first count of 2 is used to present a scenario where the number of resources is limited. The result of this scenario would show the most critical locations to locate a major rest area. These zones chosen are to be considered the areas in which facilities are prioritized. The second count of 6 is used to present the zones that represent a similar count of major rest areas identified for Scenario A. Since Scenario A uses real locations of rest areas with more than one rest area representing a particular zone, this analysis is used to show a similar count of rest areas but with one rest area per zone. This constraint may also present key areas in which rest areas are located where groups of MDCs surround a rest area. The final count of 10 is used to present a scenario with a larger number of rest areas. With this count number of major rest areas, it is expected that most MDCs will be served by nearby rest areas with minimal costs to travel. The maximum number that could be considered for the P parameter in this scenario is the total number of zones which is 426. However, the usefulness of this P parameter would be minimal because the zone selected for each MDC is the same as the location of the MDC. In other words, the lowest travel times that would be selected by the model would simply be the travel time from the centroid of the zone to the exact location of the MDC within the same zone.

Scenario C: This scenario determines the ideal zone to identify an additional rest area while maintaining the existing MRAs used from Scenario A as represented by their respective zones. The latter zones for existing MRAs will be constrained to be open in the analysis. The P parameter is set to be the number of MRAs from Scenario A plus one. For 2019, five rest areas are located in five zones. The model is run with a P parameter of 6 to constrain the model to only consider one more open zone. For 2020, the eight rest areas are located in six zones. The model is run with a P parameter of 7 to determine the additional location. This additional zone will represent the ideal location for a proposed rest area to be built for each year. The optimization does not consider the availability of land for the selected zone, and there is also potential for existing rest areas that did not meet the benchmark to already serve the coverage provided by the additional rest area.

Mathematical metrics can show how the ideal patterns are affected by incremental changes to the P parameter. The objective function represents the sum product cost of travel time and the number of trips for all origin-destination pairs as shown previously in Equation 8. In other words, a lower value will represent a better-performing case where trucks can park and rest closer to their destination.

A second performance metric is the average travel time for each OD pair and its corresponding demand for travel from the distribution centre. This time is found by multiplying each travel time by the corresponding demand, summing these values for all OD pairs, and dividing by the total demand, as shown in Equation 22 below.

$$t_{average} = \frac{\sum_i \sum_j t_{ij} D_j}{D_{total}} \tag{22}$$

where t_{ij} represents the travel time for trips between selected i and j location pairs, D_j is the total demand of trips travelling to destination j, and D_{total} is total system demand.

The third performance metric included in the analysis is the longest travel time presented in each optimized case. The maximum travel time represents how far the longest trip a truck would have to travel in the optimized result. The metric is important to show the worst trip within each optimized network as the P parameter is varied. The maximum travel time may not change as P is varied since the longest trip might remain connected to the same origin-destination pair. The equation for maximum travel time is presented in Equation 23 below.

$$t_{max} = max\{t_{ij}\} \; \forall i, j \tag{23}$$

where t_{ij} represents the travel time for trips between selected *i* and *j* location pairs.

4.6 Chapter Summary

The initial analysis in this study aims to identify general trends in freight parking activity within the region, with a focus on differences between the pre-pandemic and pandemic periods. Land use parcels are used to assess how freight parking trends vary based on the designated use of the space where trucks are parked. These parking activity patterns are then employed to identify the top 50 major distribution centres (MDCs) within the region. Again, these firms are identified for both study years for comparison. Since firms cannot be explicitly specified, they are presented by the TAZs representing them. The top 10 zones with MDCs are also compared for the two cities within the region. Various scenarios are identified to determine the top 10 firms based on the length of the parking event, the time of day the event occurs, and the day of the week.

An algorithm is applied to detect overnight parking activity that travels to MDCs the next day. These events represent the overnight parking that trucks may use to fulfill hours of service requirements, which could occur in dedicated parking facilities, unauthorized parking areas, or parking at other distribution centres. These parking stops are used to identify the major rest area facilities for 2019 and 2020. The optimization process is executed through the P-median formulation, using the gravity model to determine factors for the non-linear relationship between travel time and demand for specific facilities. Three scenarios are considered within the optimization through the P-median problem.

CHAPTER 5: PANDEMIC IMPACT ON TRUCK PARKING PATTERNS

ATRI GPS data is employed to determine where truck parking activities occur within the Region of Peel. ArcGIS software is used for visualizing the patterns of parking activities for the years 2019 and 2020. The GPS data also assists in identifying major distribution centres. After determining overnight parking activity, the origins of these trips are used to determine rest area facilities based on their destinations to major distribution centres.

5.1 Region of Peel Parking

The parking trends at the TAZ level within the region are shown in the subsequent maps using the Greater Golden Horseshoe (GGH) Model zones. The highways forming the Peel Strategic Goods Network Movement are also included in the figures to provide further context to the locations with increased activity.

Figure 9 and Figure 10 present the freight parking activity from February to July for the years 2019 and 2020, respectively, with the former depicting the period preceding the Covid-19 pandemic and the latter illustrating the period during the pandemic.

In the 2019 pre-pandemic year, as shown in Figure 9, the proportions of freight parking activity exhibit variations in distinct areas within the region. In Mississauga, a substantial portion of parking activity is concentrated in a zone represented by Point of Interest (POI) #1, located in southwestern Mississauga, accounting for 6% of the parking activity. This zone is primarily an industrial area, encompassing construction and oil and gas-based manufacturing. POI #2 represents a zone northeast of Highway 401 and Highway 410 interchange in the central part of the city, contributing to 14% of the parking activity in 2019 in Peel Region. The surrounding zones also exhibit considerable activity, ranging from 1% to 5% of total parking activity. To the east of this area lies Pearson Airport, a key facility for goods exchange in the region. POI #3 covers zones in the northwest part of the city along Highway 401, with approximately 3% of the total parking activity, predominantly within the commercial area, particularly where it overlaps with Highway 407 in the northwestern corner of the city. This area represents a secondary employment area for the city.

In Brampton, freight parking activity is primarily concentrated in the southeastern and eastern areas of the city. POI #4 presents these zones adjacent to major highways, located north of Highway 407 and east of Highway 410 in the middle of the city. However, in the northwest corner of the city, POI #5 represents the zone with the highest parking activity, contributing to 5% of all parking activity for the region. In Caledon, zones with parking activity can also be found, particularly within the Bolton industrial area in the southeastern corner of the town. POI #6 highlights this major localized and dense area of freight activity within the town, representing 1.2% of total parking activity. Additional zones with parking activity are dispersed in the rural areas north of the border with Brampton in the central part of the town and are indicated by POI #7, accounting for approximately 1.2% of total parking activity, dispersed over a larger area with two zones of interest.

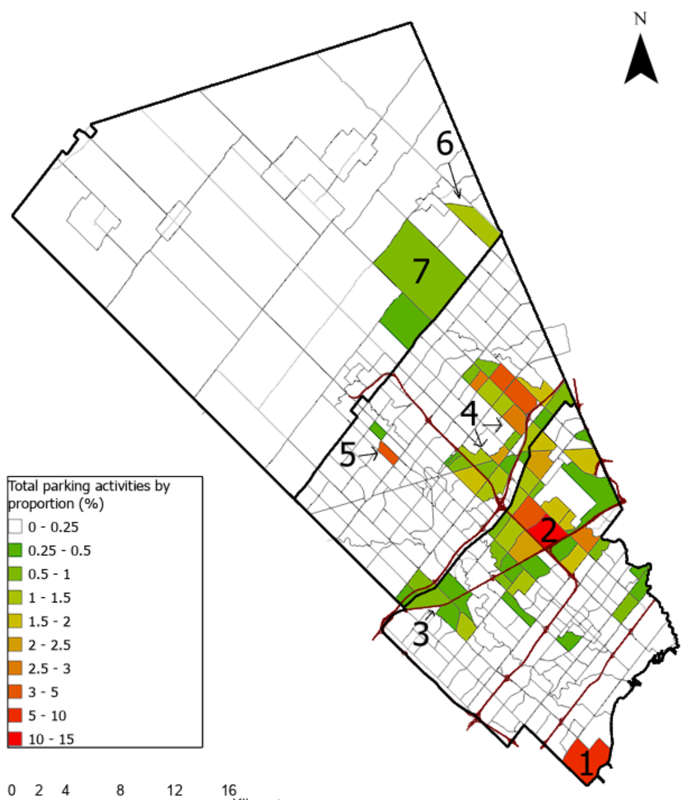


Figure 9 Parking Activity Patterns - 2019

In Figure 10, the spatial trends in freight parking activity for the pandemic year 2020 are presented. A comparison with the year 2019 reveals a dispersion of parking activity across more zones. Within Mississauga, POI #1 presents the zones to the northwest of Highway 401 and 410 interchanges, displaying a higher proportion of activity when compared to the previous year with a change of 0.5% in 2019 to 4% in 2020. In contrast, parking activity in Brampton remains relatively consistent between the years 2019 and 2020. However, the zone with the most activity for the city, indicated by POI #2, has decreased from 4.5% to 2.0% of the total parking activity, In Caledon, there is an increased proportion of parking activity within the Bolton area and the zones immediately to the west, as indicated by POI #3. A zone of interest has emerged in the western part of the town, with the growth attributed to the industrial area of Victoria, where parking within the broader zone has increased from 0.2% to 0.5% of total parking activity. POI #4 highlights the approximate location for the intersection of Hurontario and King St., serving as the main intersection of the Victoria industrial area, housing a dozen freight-related businesses surrounding the intersection that comprise most of the parking activity within the zone.

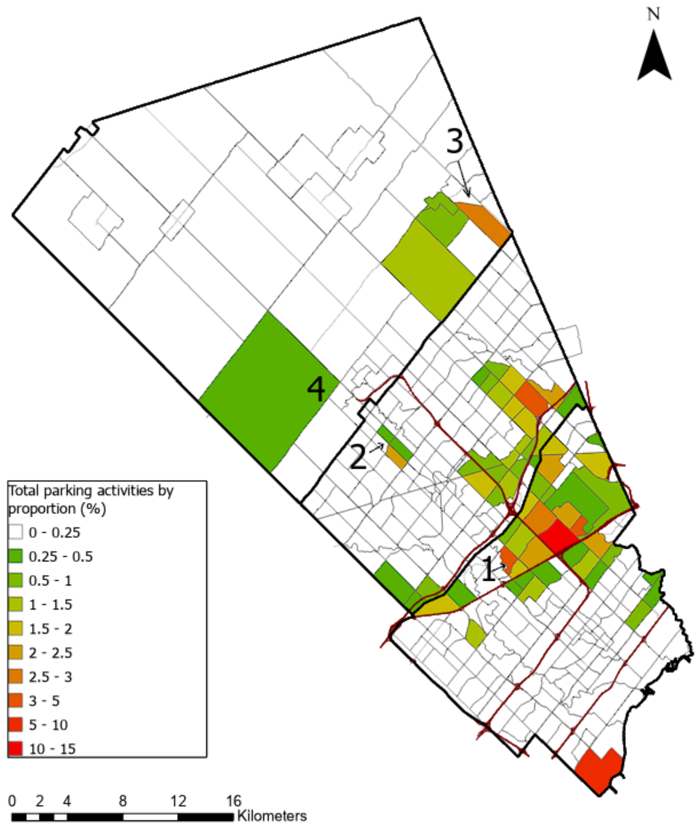


Figure 10 Parking Activity Patterns - 2020

Figure 11 illustrates the difference in freight parking activity proportions between 2019 and 2020 to emphasize their differences. This is determined by subtracting the percentage proportion in 2019 from the percentage in 2020 for each zone. In Mississauga, the zones with a higher proportion of parking activity have dispersed, particularly in the southwestern corner of the city and to the northwest of the Highway 401 and Highway 410 interchange, as indicated by POI #1 and #2. In contrast, POI #3 presents the zones in the northwest corner of the city as having higher proportions of freight activity, with an increase of about 5% distributed among the three zones. In Brampton, differences indicate a decrease in parting activity from 2019 to 2020 for 10 out of 14 zones with proportions differing by more than 0.25%. POI #4 presents the four remaining zones in the city's eastern section have an increased proportion of activity of approximately 2%. These zones include the major freight terminal at CP Intermodal Freight Terminal. As mentioned earlier, Caledon is the only municipality that has seen an increase in the proportion of parking activity from 2019 to 2020, as highlighted by POI #5 in Bolton where the proportion of freight activity has increased by about 1.75%. POI #6 and 7 indicate the remaining zones within the town have also experienced an increase in the proportion of total parking activity, ranging from 0.35% to 0.6%. Caledon stands out as the only municipality without a decrease in parking activity proportions greater than 0.25%.

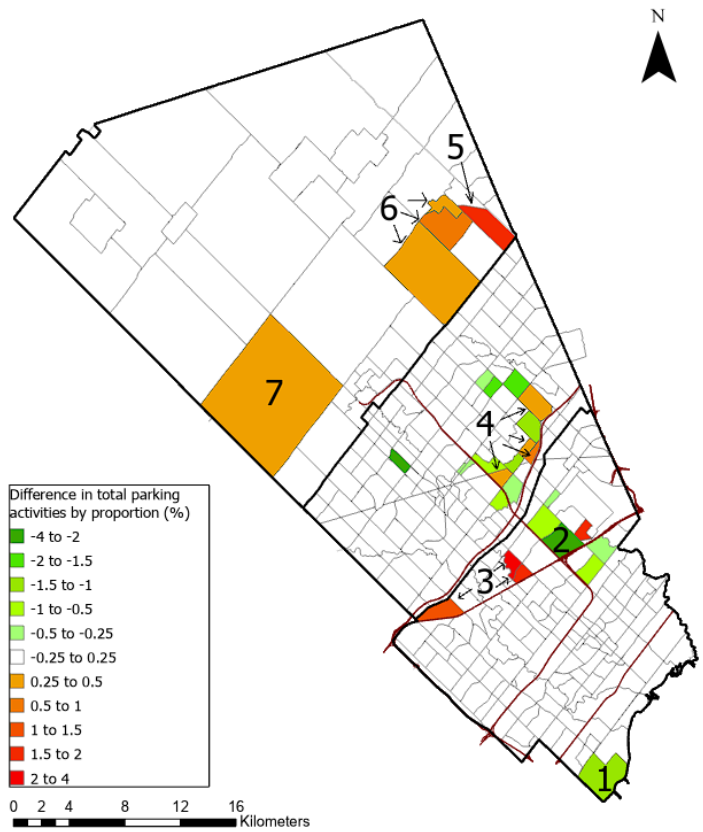


Figure 11 Difference in Freight Parking Patterns from 2019 to 2020

5.2 Parking Trends by Land Use

Next, we present the proportion of overnight freight parking by land use. The land use zones are identified from a Region of Peel shapefile at the parcel level for 2019. The parking results are joined with these parcels. Figure 12 below provides a breakdown of parking activities per land use category for the 2019 and 2020 years in the City of Mississauga, representing the percentage based on the total observed parking activities for each year. The full names of these land uses are detailed in Chapter 4.2.

The majority of truck parking occurs in industrial land use zones. However, some trends between the two years have emerged. In the pre-pandemic year of 2019, truck parking events in parcels with office land use accounted for 1.34% of the data. In 2020, parking events in the same land use are dropped to 0.72%, marking a 46% reduction from the previous year. Another change observed in Mississauga is the increased proportion of data associated with vacant land. The percentage of parking activities rose from 0.16% to 0.63%. Upon examining parcels with this land use through satellite imagery provided via ArcGIS, it is evident that some areas either serve as makeshift parking areas or more dedicated parking spaces for trucking activities, especially in construction. In other words, since the land use is designated for 2019, there may be new areas with different designations representing 2020. Alternatively, trucks may be parking on vacant land that has not been designated for parking.

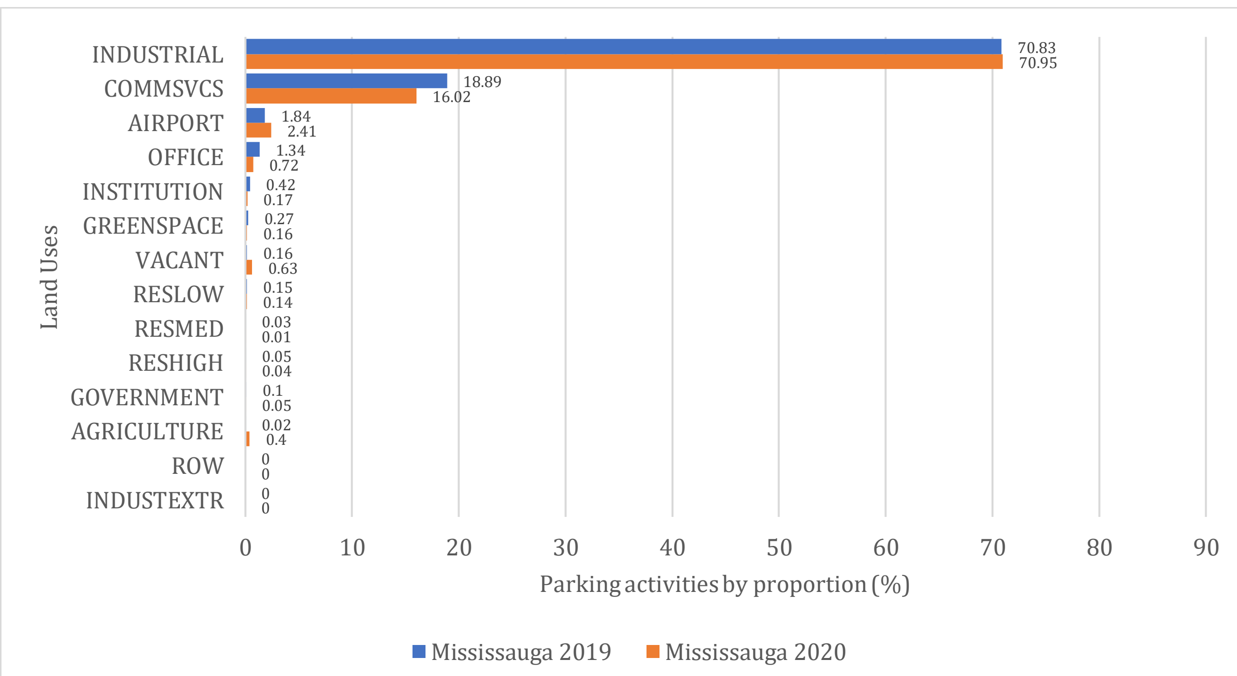


Figure 12 Parking Activities per Land Use - Mississauga

Figure 13 provides the parking activities per land use for Brampton for 2019 and 2020. As seen in Mississauga, similar increases are observed for parking on vacant land, alongside a decrease in parking on office-designated land. The land uses are presented as descriptors of property parcels within the region at the parcel level. Only one parcel exists within the city that matches the industrial area with a quarry/pit (INDUSTEXTR) but that parcel also contains a truck parking stop. This parcel exhibited a decreasing proportion from 2019 to 2020.

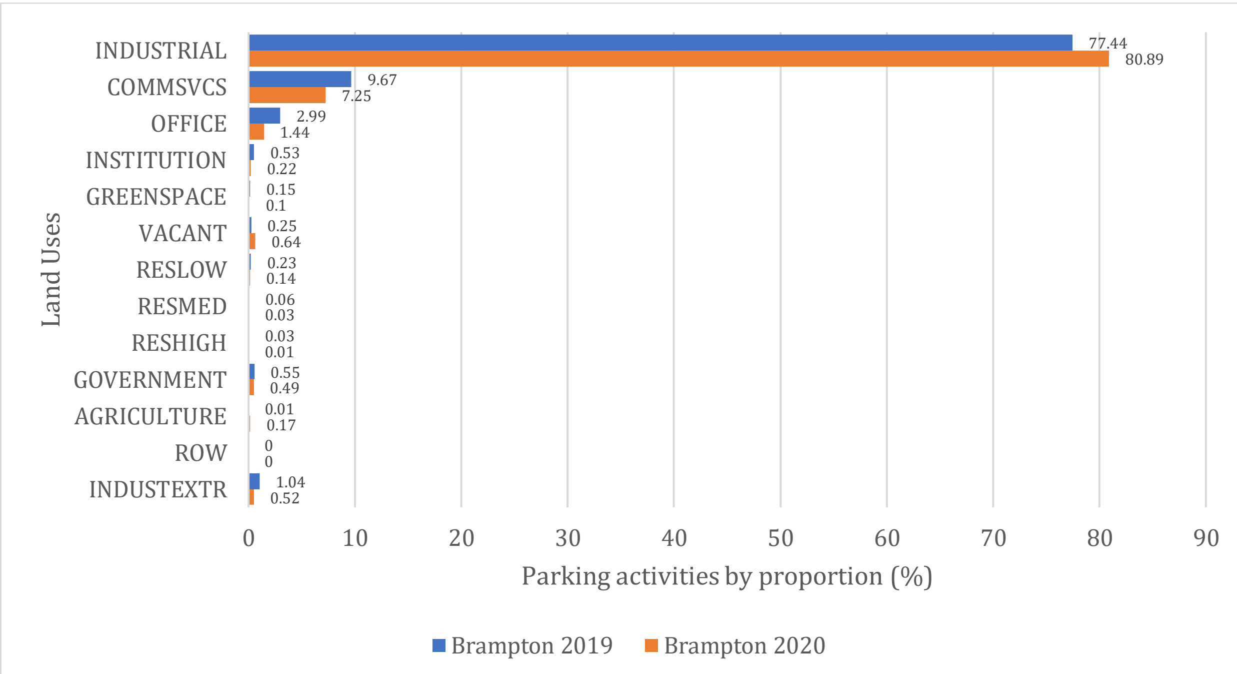


Figure 13 Parking Activities per Land Use - Brampton

Figure 14 presents the parking activities by land use for Caledon in both 2019 and 2020. Caledon exhibits a more pronounced decrease in parking activities associated with office land use. There are fewer office firms in this town than in the other two municipalities, and the pandemic restrictions may have played a heavy role in this observed reduction. Another observed trend is the reduction from 3.5% to 1% in government land use between the two years. The change is mainly attributed to a reduction in truck parking at the Region of Peel Curing Facility. Low-density residential land possesses a truck parking proportion of 2.88% in 2019 and 2.67% in 2020. Caledon's residential lots are typically larger than those lots in similar land use in the other two municipalities and can therefore accommodate trucks as they use a piece of land from their lots to store freight vehicles. Zoning bylaws for residential land indicate that this parking is unauthorized unless the owners hold exemptions.

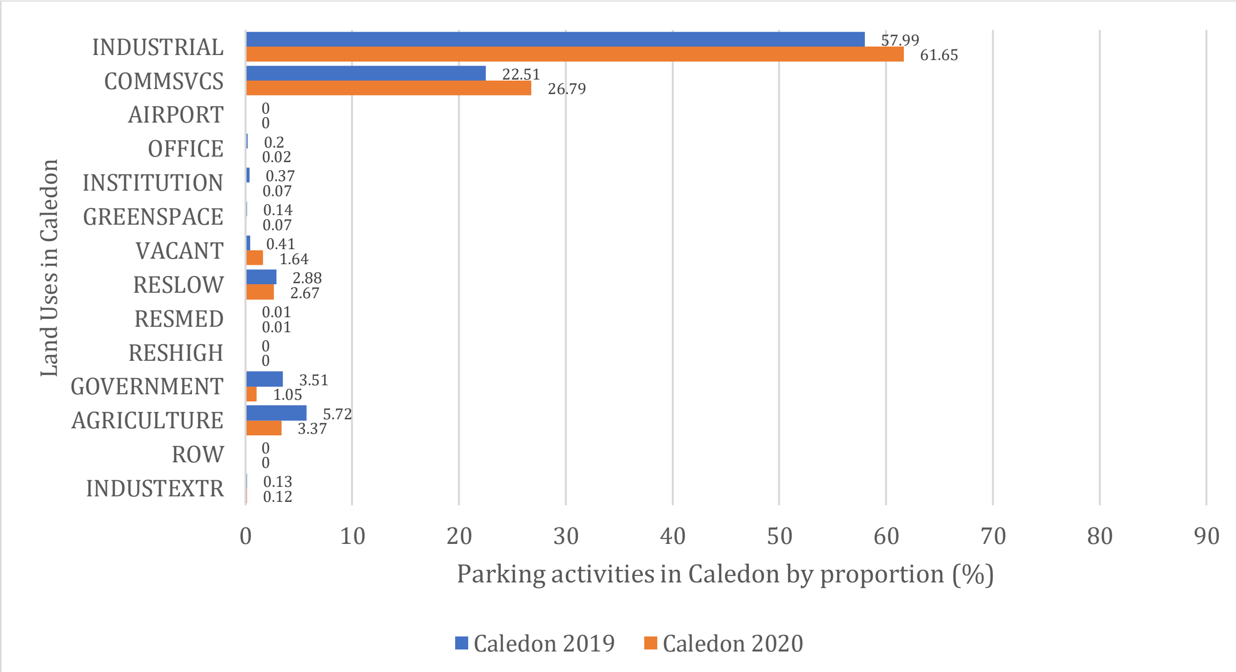


Figure 14 Parking Activities per Land Use - Caledon

5.3 Zone Ranking of Major Distribution Centres

After analyzing general freight parking trends across the region, specific firms are also identified. Using the parcels provided by Teranet, the top 50 DC firms, also known as MDCs, are obtained through a join process.

5.3.1 Top MDCs in the Region of Peel

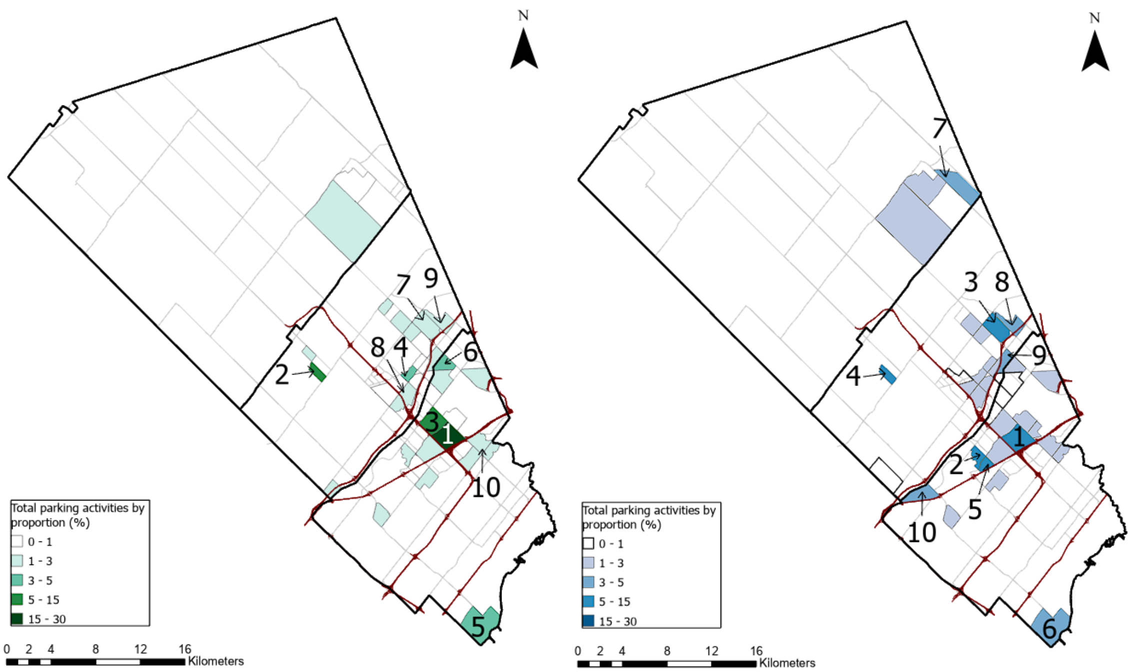
The top 50 MDCs with the highest parking activity in the region for each year are discussed in this section. Figure 15a and Figure 15b represent the top 50 MDCs based on the number of parking activities for 2019 and 2020, respectively. The comparisons between the firms at the parcel level are not allowed due to data restrictions. The parcels representing the firms are joined to the TAZs to present the locations of these firms. The top 10 TAZs with MDCs are also noted within this figure. The top 10 zones represented 21 of these top 50 firms in 2019 and 22 of these top 50 firms in 2020. Table 2 below provides a breakdown of the top 10 zones in 2019 and 2020. Appendix A provides a complete list of results by TAZ.

The top 10 TAZs with MDCs in 2019, presented on the left side of Table 2, account for 67% of all freight parking activity at MDCSs within the region. The top 10 is represented by 5 zones in the City of Mississauga, 5 zones in the City of Brampton, and 0 locations in Caledon. The absence of the latter jurisdiction on this list is expected due to the smaller scale of economic activity. Although the number 1 location in 2019 is located near two major freeways at Highway 401 and 410, the zone with the second most parking activity by DCs in a more remote area west of Highway 410 in Brampton. The 3rd and 4th zones are centralized freight areas in Brampton and Mississauga. However, the 5th zone is within the southwestern corner of Mississauga, which is more remote but is not far from the Queen Elizabeth Way.

The right side of Table 2 presents the results for the year 2020. The #1 zone coincides with the same #1 zone in 2019. However, the results in 2020 represent a smaller proportion of total parking activity from 7.6% to 4.3% but with more top firms identified within this zone. Zone #2 is northwest of Highways 401 and 410 interchanges and represents one firm with 4% of the total parking activity. This MDC describes the most parking activity within the region from a single firm. This MDC describes the most parking activity within the region from a single firm. In contrast, Zone #2 for 2020 is not in the top 10 for 2019 but within the top 11-15.

The #3 and #4 zones in 2020 are located in the City of Brampton and represented the #7th and #2 zones in 2019. The #3 zone is in eastern Brampton and is in proximity to Highway 407 and to the north of Pearson Airport. This zone also represents the CN Intermodal Terminal within Brampton, a major hub for exchanging goods between land and rail freight. The #4 zone is located in a western zone previously identified as #2 in 2019. A larger proportion of parking activity is within this zone in 2020 even though the ranking is lower. The #6 zone in 2020 corresponds to the #5 zone in 2019, representing an industrial area in Mississauga's southwestern corner. The #7 zone is the only top zone in the Town of Caledon. This zone corresponds to a large freight and industrial area in the Bolton community. This corresponds with increased freight activity within Caledon in 2020 compared to the previous year. The #8 and #9 zones in the City of Brampton are close to each other and close to the #2 zone. The #10 zone is located further away in northwestern Mississauga and corresponds to a secondary industrial or employment location within the city. This area is designated as a secondary employment area for Mississauga compared to the zones that surround Pearson Airport in the east that represent the most activity.

In summary, the #1 zone between the two years is the same, but a reduction is evident in the proportion of parking activity at MDCs. The reduction is noted by a shift of parking activity from the #1 zone to the remaining zones in the top 10.



a) 2019 b) 2020

Figure 15 Top 50 MDCs in the Region of Peel

Table 2 Top 10 TAZs for MDCs in the Region of Peel in 2019 and 2020

2019 TAZ Rank	City	MDC Count	2019 Parking*		2020 TAZ Rank	City	MDC Count	2020 Parking**
1	Mississauga	4	26.18%		1	Mississauga	5	13.44%
2	Brampton	1	10.46%		2	Mississauga	1	11.78%
3	Mississauga	2	6.78%		3	Brampton	2	6.73%
4	Brampton	2	4.94%		4	Brampton	1	5.29%
5	Mississauga	2	3.73%		5	Mississauga	2	5.10%
6	Mississauga	3	3.51%		6	Mississauga	3	4.22%
7	Brampton	1	2.92%		7	Caledon	3	3.65%
8	Brampton	2	2.78%		8	Brampton	3	3.62%
9	Brampton	3	2.74%		9	Brampton	1	3.41%
10	Mississauga	1	2.70%		10	Mississauga	1	3.04%
Total		21	66.73%		Total		22	60.27%

*The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs in Peel Region in 2019
**The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs in Peel Region in 2020

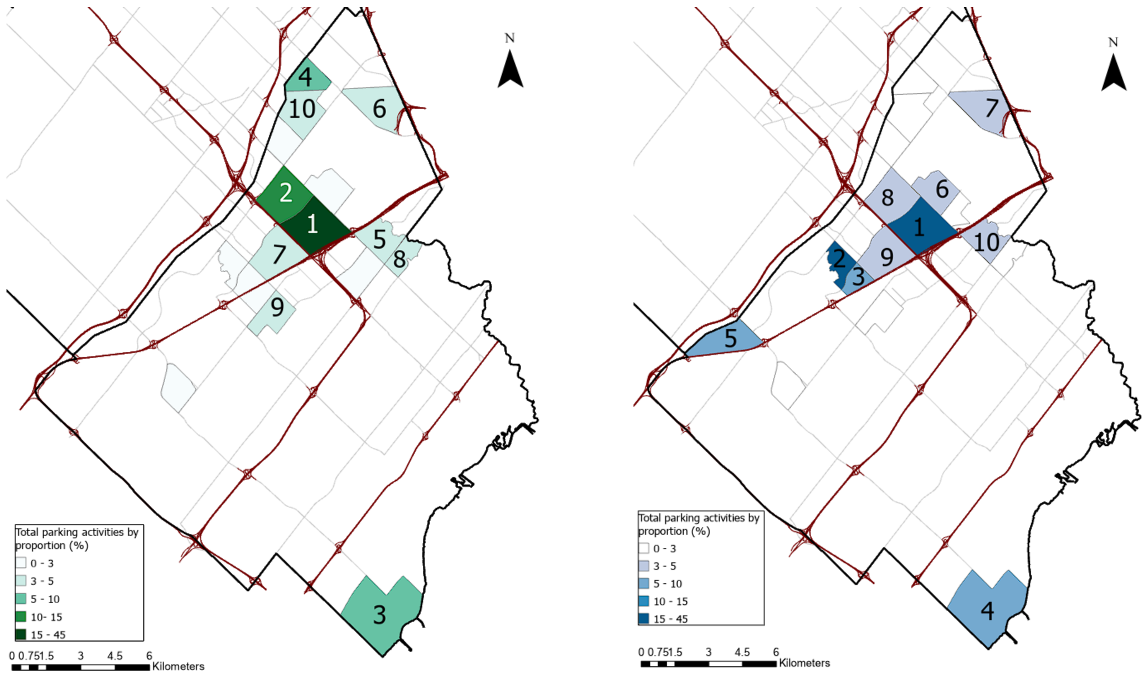
5.3.2 Top MDCs in Mississauga

Figure 16 below presents the top 10 zones with MDCs in Mississauga in 2019 and 2020. The top 10 zones are again denoted on the maps. Table 3 presents the percentages of total parking activities within MDCs for each zone in 2019 and 2020, respectively.

Based on Figure 16a and Table 3, most of the top 10 zones within Mississauga are located around Pearson Airport. The top two zones represent 6 MDCs and 16.6% of the total parking activity within the city. The third zone represents the city's southwestern corner and represents 2% of Mississauga's parking activity. The remaining seven zones surround the airport except for #7 and #9 zones, which are immediately west of Highway 410 and 403.

Based on Figure 16b and Table 3, most of the top 10 zones within Mississauga in 2020 are north of Highway 401. The top 2 zones represent 6 MDCs but represent 13.2% of the total parking activity. The zone #3 is located to the south of zone #2. Compared to 2019, there is more representation in the western zones within the city. However, zones #6, 7, 8 and 10 surround the airport further indicating the importance of the air cargo facility.

When contrasting the two years for this city, a shift westward is observed from the airport area to zones west of Highway 410/403, though many parking events still congregate around Pearson Airport. Furthermore, both years have these top 10 zones representing 90% of all MDC parking in Mississauga.



a) Top 10 in 2019 b) Top 10 in 2020

Figure 16 Top 10 TAZs for MDCs in Mississauga

Table 3 Top 10 TAZs for MDCs in Mississauga in 2019 and 2020

2019 TAZ Rank	**MDC Count**	**2019 Parking***		**2020 TAZ Rank**	**MDC Count**	**2020 Parking****
1	4	44.07%		1	5	22.80%
2	2	11.41%		2	1	19.98%
3	2	6.27%		3	2	8.65%
4	3	5.90%		4	3	7.16%
5	1	4.54%		5	1	5.16%
6	1	3.80%		6	1	4.51%
7	2	3.60%		7	2	4.45%
8	1	3.41%		8	1	3.46%
9	1	3.34%		9	1	3.38%
10	2	3.02%		10	1	3.24%
Total	19	89.37%		Total	18	82.79%

*The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs in Mississauga in 2019
**The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs in Mississauga in 2020

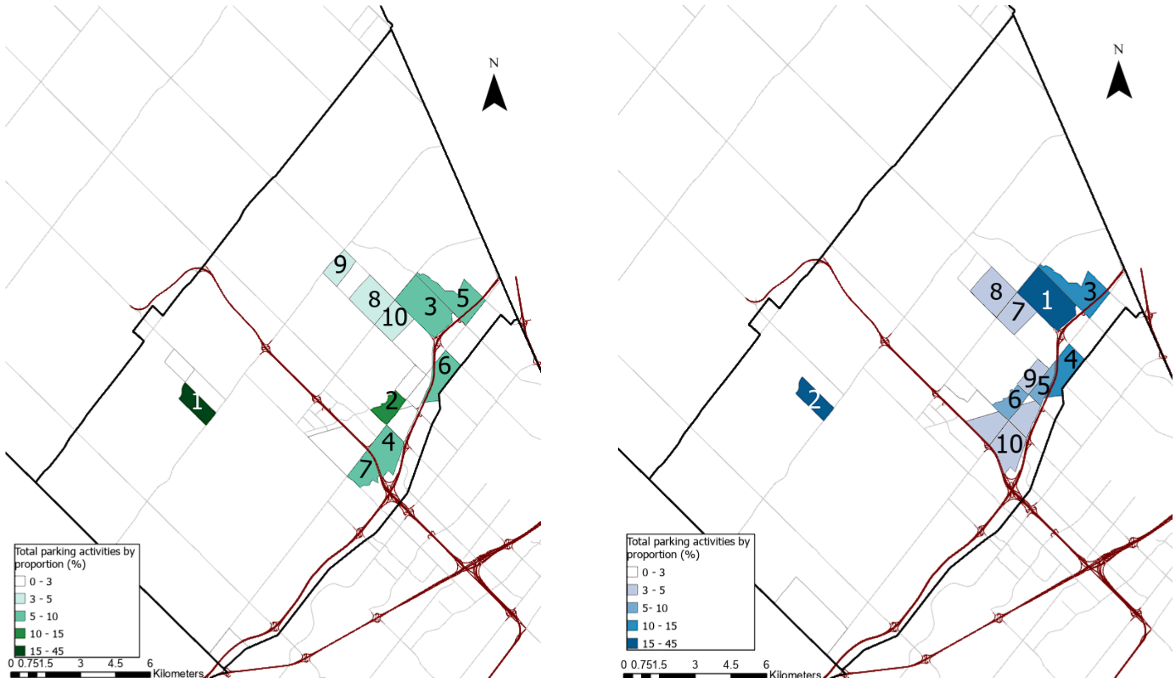
5.3.3 Top MDCs in Brampton

Figure 17 shows that most MDCs in Brampton are positioned near Mississauga and close to Highway 407 for both years. Table 4 presents the tabular results.

Based on the results shown in Figure 17a, the top ten zones with MDCs in 2019 except for zones #1 and #7 in the city's eastern area, with the #1 zone possessing the most activity is in the western area of Brampton. Based on Table 4, this top zone represents almost 27% of MDC parking activity in Brampton. Zone #2 has 13% of parking activities in Brampton and is located close to Highways 410 and 407. Zone #3 is in the city’s eastern area and corresponds to the CN Intermodal Terminal with 7.5% of MDC parking activity. The remaining seven zones are located near Highway 407 north of Pearson Airport. Similar to Mississauga, the top 10 zones represent 85% of all parking activity in the city.

Figure 17b shows a similar pattern to 2019 with the top 10 zones located in the city's eastern area with zone #2. However, based on Table 4, zone #1 for 2020 corresponds to the CN Intermodal Terminal. This zone represents 20% of the 2020 parking activity compared to 7% of activity in 2019 with an inclusion of an additional MDC in the zone in 2020. The intermodal terminal may have been a key facility of use during the pandemic period when compared to the previous year. However, the #1 zone in 2019 possessed 25% of total MDC parking. Therefore, the top 2 to 10 zones possess a higher proportion of MDC parking activity in 2020.

Caledon only possesses 2 zones with MDCs in 2019 and 3 zones with MDCs in 2020 and are not mapped individually. However, these firms are still considered in the optimization process for further analysis.



a) Top 10 in 2019 b) Top 10 in 2020

Figure 17 Top 10 TAZs for MDCs in Brampton

Table 4 Top 10 TAZs for MDCs in Brampton in 2019 and 2020

2019 TAZ Rank	MDC Count	2019 Parking*		2020 TAZ Rank	MDC Count	2020 Parking*
1	1	26.85%		1	2	19.84%
2	2	12.68%		2	1	15.59%
3	1	7.48%		3	3	10.67%
4	2	7.13%		4	1	10.06%
5	3	7.02%		5	1	6.84%
6	1	6.31%		6	1	6.74%
7	2	6.08%		7	1	4.99%
8	2	4.83%		8	1	4.25%
9	1	4.30%		9	1	4.03%
10	1	3.05%		10	1	3.41%
Total	16	85.73%		Total	13	86.40%

*The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs in Brampton in 2019
**The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs in Brampton in 2020

5.4 Additional MDC Zone Rankings

The parking activity is segmented by category in this section based on parking duration, time of day, and day of week.

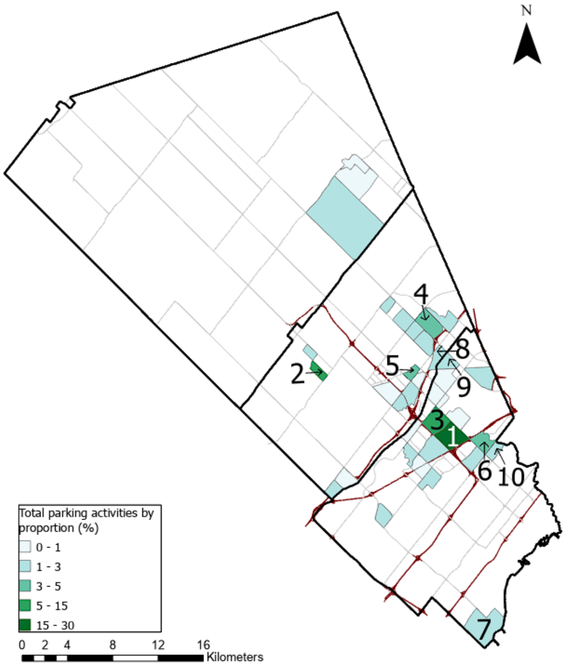
5.4.1 Parking Duration

This section builds on the previous analysis to filter and compare results for parking events with durations less than two hours and greater than 2 hours. The duration is selected to coincide with important off-duty requirements required by the Motor Transport Act (2019). A daily off-duty time for a driver requires 10 hours, which must include an 8-hour consecutive block of time. Parking durations of less than 2 hours can be used to make up the rest of the time with shorter breaks as small as 30 minutes. A truck parking during a trip for longer than 2 hours is subsequently fulfilling the larger 8-hour block required for resting.

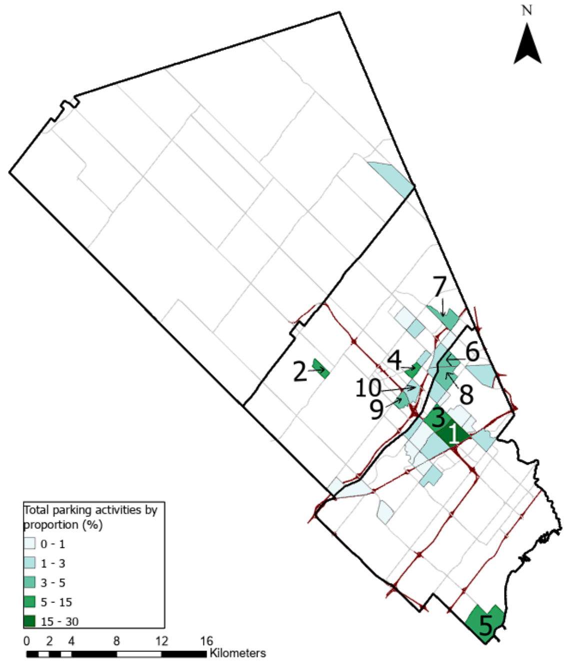
Figure 18 presents the top 50 DCs based on parking activities with a duration of less than or equal to 2 hours and compares them with activities greater than 2 hours. Table 5 provides the tables to compare the firms between the two cases for 2019 and 2020, respectively.

When examining Figure 18a, Figure 18b, and Table 5, a comparison of MDCs within the 2019 year based on parking duration is discussed. The differences between short-duration and long-duration parking are quantified with the top 10 zones for short duration representing 63% of the MDC parking of short duration compared to 77% of long-duration MDC parking occurring in the top 10 zones. In other words, the firms within the top 10 zones for long-term parking represent a larger proportion of parking compared to the top 10 zones for short-term parking. Spatially, both categories appear to be similar with the top 3 zones being identical in location between them. The remaining zones in the top 10 for both categories are within southeastern Brampton, northeastern Mississauga and the one zone in the southwestern Mississauga corner.

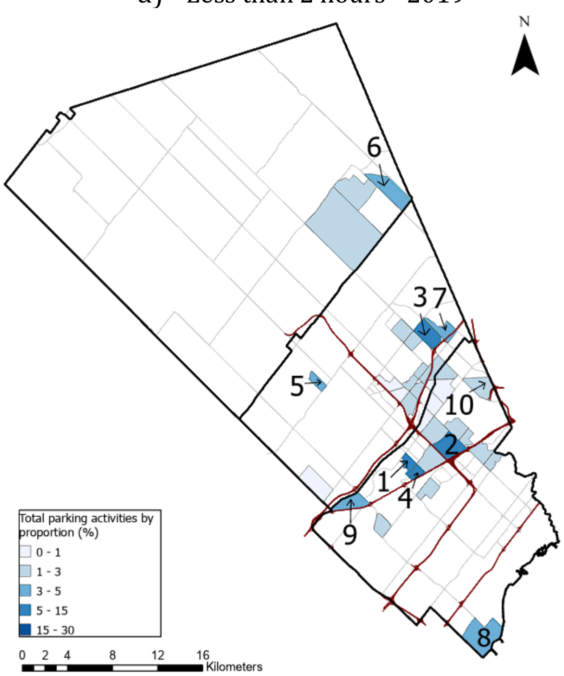
When examining Figure 18c, Figure 18d, and Table 5, a comparison of MDCs within the 2020 year based on parking duration is discussed. The proportion of the difference between short-duration and long-duration parking is less this year with the difference between the top 10 zones being 7.5% this year compared to 14.5% in the previous year. However, spatially there are differences where zones #4 and #9 in northwestern Mississauga and zone #6 in Caledon for short-duration parking are not within the top 10 for long-duration parking. This indicates that firms within these zones may have restrictions that prevent them from parking for long durations.



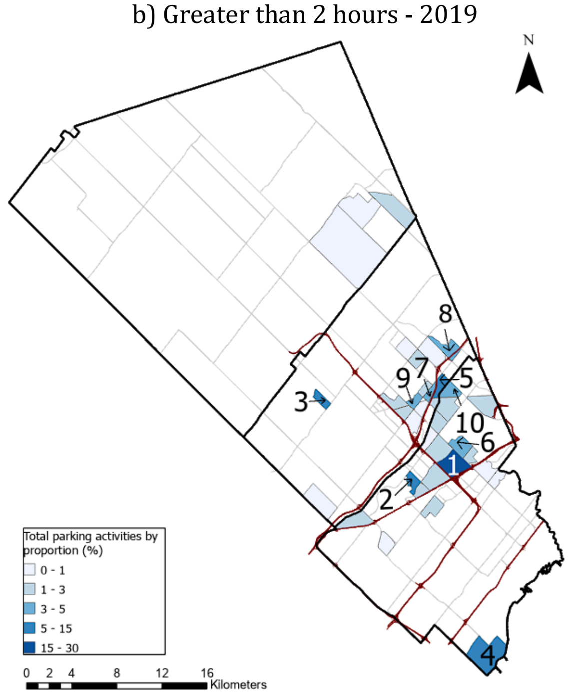
a) Less than 2 hours - 2019



b) Greater than 2 hours - 2019



c) Less than 2 hours - 2020



d) Greater than 2 hours - 2020

Figure 18 Top 50 MDCs by Parking Duration in the Region of Peel

Table 5 Top 10 TAZs for MDCs by Parking Duration in the Region of Peel

TAZ Rank*	2019 Parking <2hrs**	2019 Parking >2hrs**	2020 Parking <2hrs**	2020 Parking >2hrs**
1	25.69%	25.55%	12.42%	20.71%
2	8.45%	14.32%	11.23%	9.69%
3	6.61%	6.62%	8.54%	7.49%
4	4.00%	6.06%	6.21%	6.74%
5	3.89%	5.25%	4.62%	5.21%
6	3.37%	4.74%	4.23%	4.56%
7	2.95%	4.39%	3.69%	3.97%
8	2.86%	3.64%	3.45%	3.39%
9	2.86%	3.52%	3.31%	3.18%
10	2.72%	2.92%	2.94%	3.17%
Total	63.40%	77.01%	60.64%	68.11%

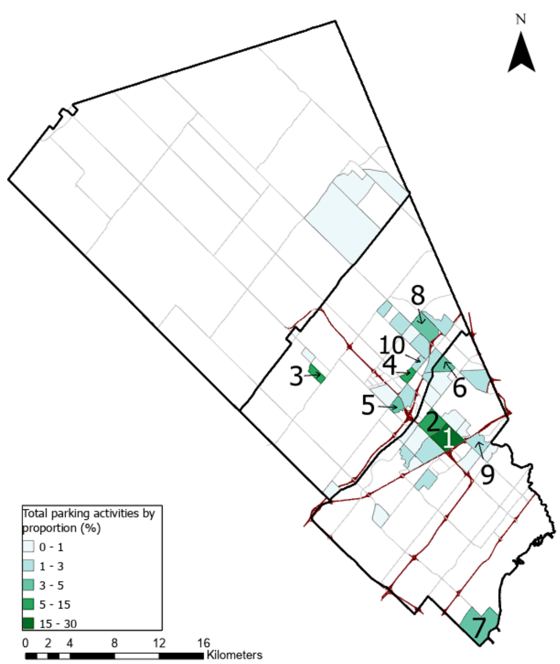
*The zone rank corresponds to the zones per each category in Figure 18
**The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs per each category in Figure 18

5.4.2 Time of Day

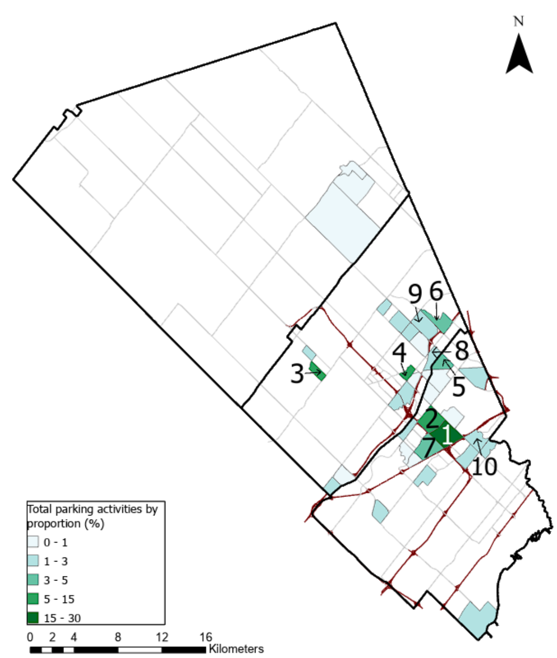
The next analysis investigates the time of day for stops by time of day. This includes the AM peak with parking activity ending in the morning between 6 am to 9 am and the PM peak for parking activity that ends in the evening from 4 pm to 7 pm. The end of the parking activity aligns with the next chapter focusing on the optimization of trips occurring after a break at a rest area and travelling to an MDC. The peak periods also align with periods of highest traffic congestion when conditions are typically the most difficult for road users.

Figure 19 below presents the top 50 DCs based on the time of day in 2020. Table 6 provides the tables to compare the firms between the two years of 2019 and 2020. When examining Figure 19a, Figure 19b, and Table 6, a comparison of the top MDCs based on the peak periods of the day for 2019 is discussed. However, there are not many differences between the two time periods spatially, with 6 out of the top 10 zones being mutual between the two categories with different rankings. The top 4 zones are the same between the two categories. However, the 7th zone in the AM peak is not a top 10 zone in the PM peak which may indicate that firms within this zone favour travel in the morning compared to the afternoon. Quantitatively, there is only a 4% difference between the proportion of MDC parking activity for the top 10 zones in each category.

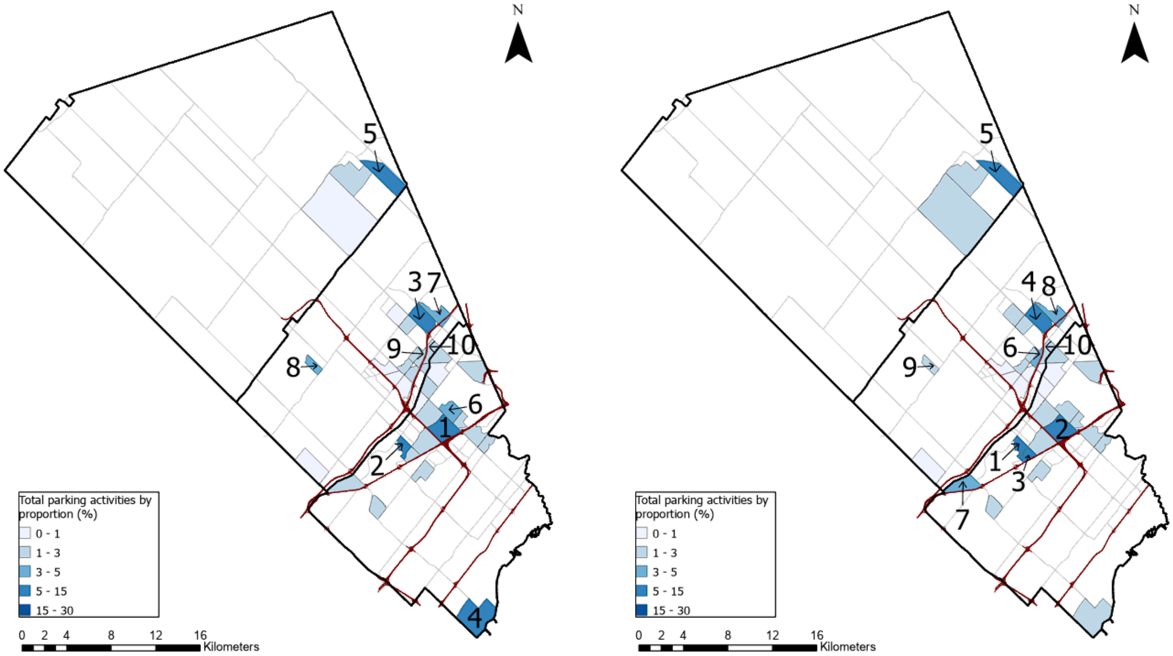
A comparison of the top MDCs based on the peak periods of the day for 2020 is shown in Figure 19c, Figure 19d, and Table 6. Within this year, 8 out of the top 10 zones are located at the same locations with different rankings. Similar to the previous year, the zone in southwestern Mississauga which is 4th in the AM Peak is not included in the top 10 for the afternoon. This discrepancy is consistent between both years indicating that MDCs within the southwestern part of the city favour travel in the morning compared to the afternoon. However, when comparing year to year, the #1 zone represents only 13% in 2019 compared to 25% in 2020.



a) 2019 AM Peak



b) 2019 PM Peak



c) 2020 AM Peak

d) 2020 PM Peak

Figure 19 Top 50 MDCs by Time of Day in the Region of Peel

Table 6 Top 10 TAZs for MDCs by Time of Day in the Region of Peel

TAZ Rank*	2019 AM Parking**	2019 PM Parking**	2020 AM Parking**	2020 PM Parking**
1	24.88%	24.66%	13.59%	13.43%
2	8.53%	9.16%	11.49%	12.20%
3	6.76%	7.25%	9.03%	7.63%
4	6.72%	5.66%	6.28%	6.08%
5	4.88%	4.13%	5.70%	5.13%
6	4.63%	3.97%	4.31%	4.48%
7	4.36%	3.24%	3.89%	4.11%
8	4.21%	2.95%	3.47%	3.34%
9	2.75%	2.94%	2.69%	2.93%
10	2.63%	2.63%	2.59%	2.84%
Total	70.35%	66.59%	63.04%	62.17%

*The zone rank corresponds to the zones per each category in Figure 19

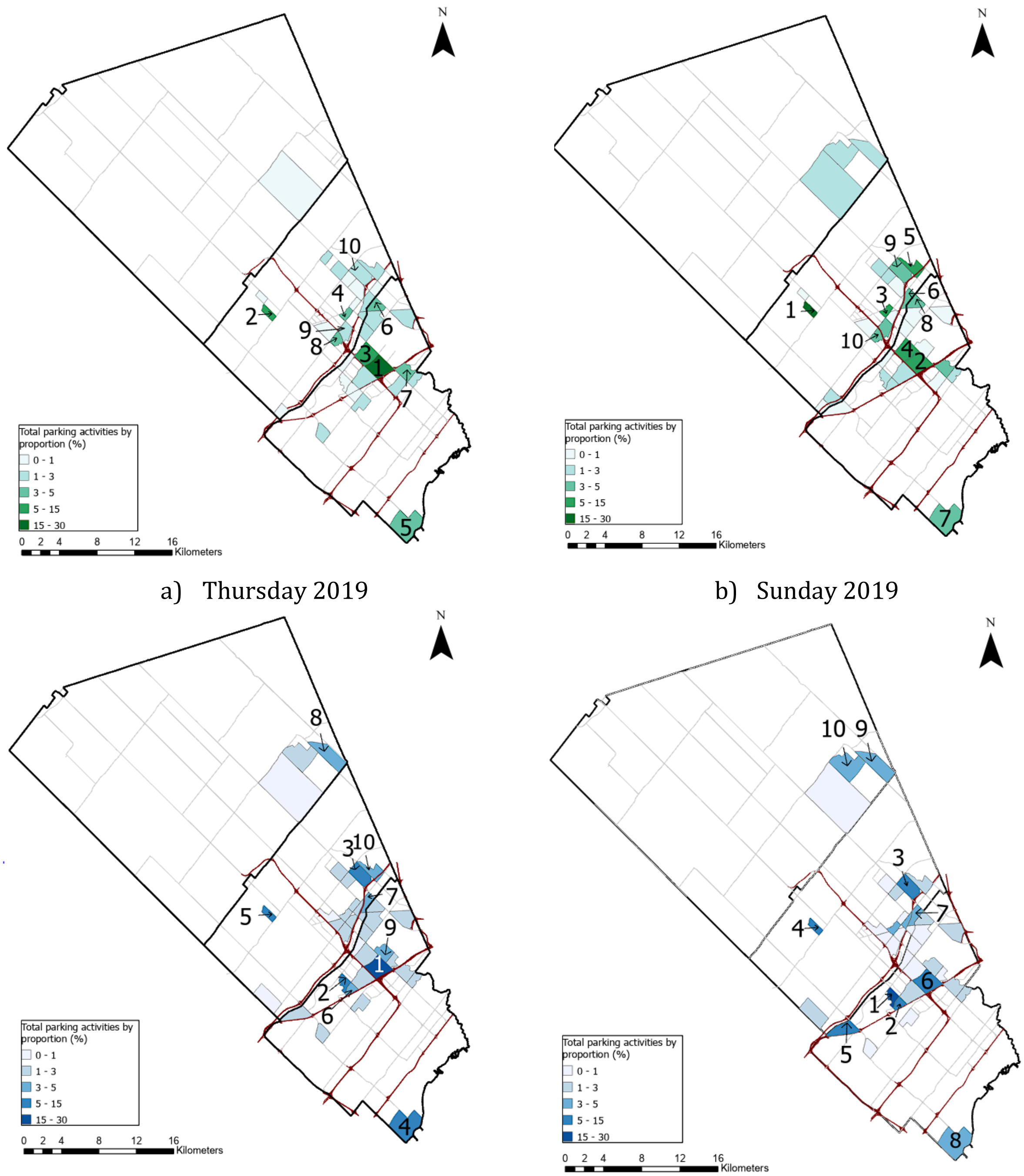
**The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs per each category in Figure 19

5.4.3 Day of Week

This section analyzes differences observed for weekday and weekend activities. The distinction between these two types of days is important due to the closure of MDCs based on non-operation during the weekend. Thursday and Sunday are selected for this purpose. Thursday represents the weekday containing the most activity in the dataset while Sunday contains the least amount of activity. Other days of the week are beyond the scope of the thesis for this particular analysis due to the selected days of Thursday and Sunday being representative of the two categories of days. Figure 20 presents the top 50 MDCs based on Thursday and Sunday. Table 7 provides the lists to compare the firms between the days for 2019 and 2020.

When examining Figure 20a, Figure 20b, and Table 7, a comparison of the top MDCs based on the day of the week for 2019 is discussed. Similar to the previous comparison of time of day, out of the top 10 zones are mutual between the two days of weekday and weekend. However, the ranking between the two days is different between the two days. For example, the #1 zone on Thursday with 27% of MDC parking activity becomes the #2 zone with 14% which indicates that the parking activity on the weekend occurs in the remaining zones. For example, the #2 zone on Thursday with 10% of the activity becomes the #1 zone on Sunday with 15%. The top 10 zones represent more of the parking activity on Sunday compared to Thursday with 72% of the Sunday parking activity present in the top 10 zones compared to 68% on Thursday. The limited number of firms that are open on weekends explains why more of the parking activity is allocated to the top number of firms.

When examining Figure 20c, Figure 20d, and Table 7, a comparison of the top MDCs based on the day of the week for 2020 is discussed. Within this year, the top 10 zones show differences with 7 out of the 10 zones being mutual between the two days. The #3 and #7 zones are mutual for the same year. However, quantitatively, the #1 zone goes from 16% on Thursday to 6% on Sunday parking data as the #6 zone. The #2 zone on Thursday with 10% of MDC parking on that day becomes the #1 zone with 20% of Sunday MDC parking. Again, the closure of firms on weekends explains the shift in the proportion of parking from the #1 zone to the remaining zones.



a) Thursday 2019 b) Sunday 2019

c) Thursday 2020 d) Sunday 2020

Figure 20 Top 50 MDCs by Day of Week in the Region of Peel

Table 7 Top 10 TAZs for MDCs by Day of Week in the Region of Peel

TAZ Rank*	Thursday 2019 Parking**	Sunday 2019 Parking**	Thursday 2020 Parking**	Sunday 2020 Parking**
1	27.15%	15.11%	15.85%	20.85%
2	10.58%	13.54%	10.10%	9.54%
3	6.32%	10.05%	5.90%	6.49%
4	4.61%	7.67%	5.42%	5.71%
5	4.39%	6.39%	5.28%	5.61%
6	3.56%	4.71%	3.97%	5.39%
7	3.33%	4.30%	3.68%	4.02%
8	3.21%	3.59%	3.50%	3.77%
9	2.9%	3.46%	3.47%	3.45%
10	2.52%	3.25%	3.46%	3.33%
Total	68.57%	72.07%	60.63%	68.16%

*The zone rank corresponds to the zones per each category in Figure 20
**The percentage is based on the ratio of parking events at the TAZ to the total parking events at MDCs per each category in Figure 20

5.5 Overnight Parking and Rest Area Facilities

After applying the criteria for overnight parking mentioned in Chapter 4 approximately 15,700 overnight events were observed in 2020 and approximately 7,600 events in 2019. The rest areas are later used as origin points for the optimization discussed in the next chapter.

Figure 21 and Figure 22 below present the locations of these events at the TAZ level. Based on Figure 21, overnight parking trends in 2019 show that this type of parking occurs in areas surrounding the major freeways within the region. Similar to the previous analysis, POI #1 presents the zone northeast of Highway 410 and 401 that has the highest proportion of activities with 14% of the total overnight parking. Zones adjacent to this particular zone also possess increased proportions of activity. POI #2 also presents the zone in southwest Mississauga and POI #3 west of the Bolton industrial area within Caledon and both zones have large proportions of parking activities in remote areas. Certain zones in Brampton have a 2-5% of the overnight parking activity that surrounds Highway 410 indicated by POI #4. POI #5 in the southeast of Brampton also possesses overnight parking activity between 1 and 3%.

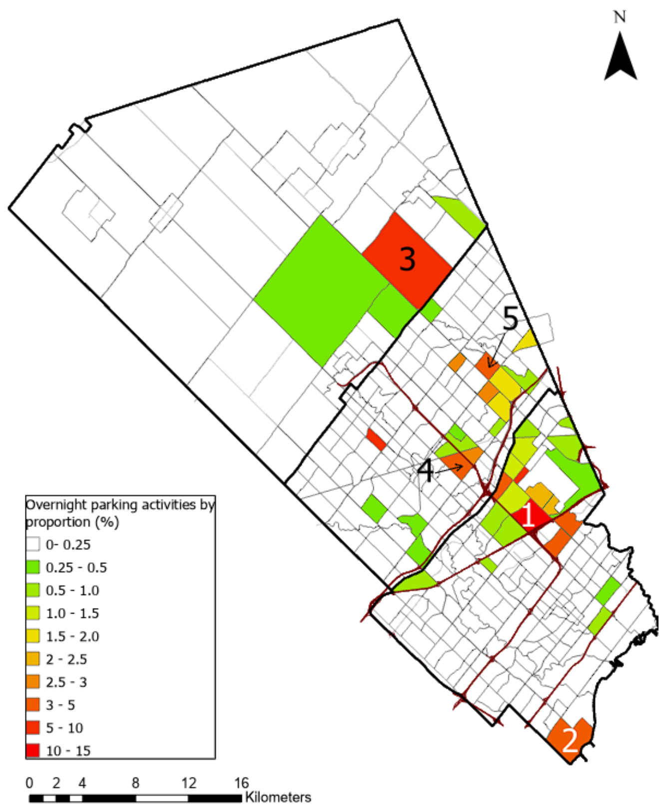


Figure 21 Overnight Parking at TAZ – 2019

Figure 22 shows overnight parking trends in 2020. The overall trend is similar to the previous year However, the areas surrounding the 401/410 interchange possess 4 zones in 2020 with an increased proportion of overnight parking activity. There is a decrease in the proportion of overnight parking activity in Brampton north of the airport in the east as noted in POI #2, but POI #3 presents zones near Highway 410 interchanges that retain the same proportion of activity from 2019. Southwestern Mississauga still possesses a large amount of overnight parking activity as noted in POI #4 with 6% of the total overnight parking. However, Caledon shows differences between the two years, with the overnight activity occurring in the south-central portion of the town noted in POI #5 reducing from 9% of the overnight parking activity in 2019 to 2% in 2020. The zones representing Bolton and surrounding areas, as indicated in POI #6, have increased levels of overnight activity with more nearby MDCs in the area for this year as indicated previously by Table 2.

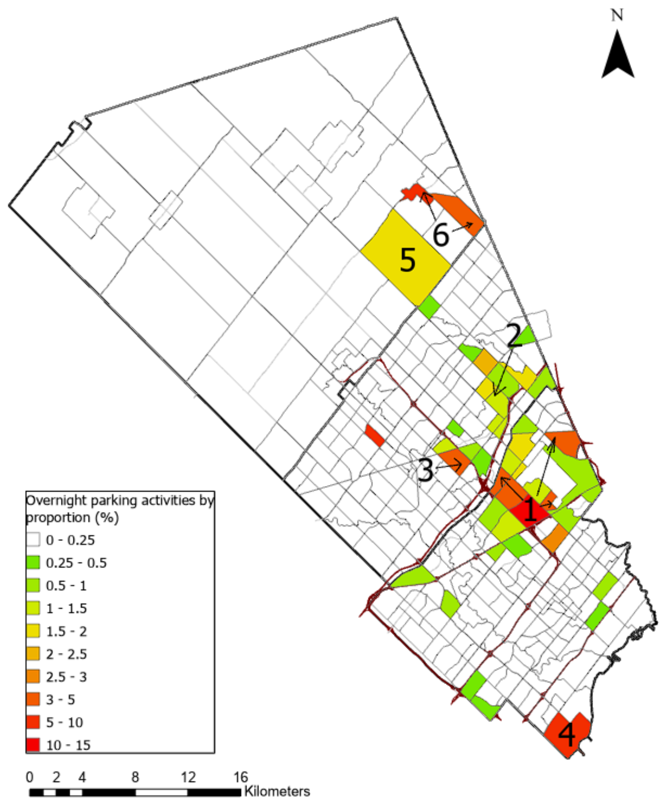


Figure 22 Overnight Parking at TAZ – 2020

The differences in proportional rates from 2019 to 2020 are explicitly shown in Figure 23 below. As noted earlier, more areas surrounding the Highway 401 and 410 interchange area have increased levels of overnight parking activity in 2020 with select zones increasing in proportion by 2-3%. The proportion of activity within southwestern Mississauga also has increased in the proportion between the two years with an increase in proportion by 2%. Central Caledon and regions north of Pearson Airport within Brampton have reductions that range from 1-6% proportionally, while the Bolton area possesses observed increases with an increased proportion of 3%.

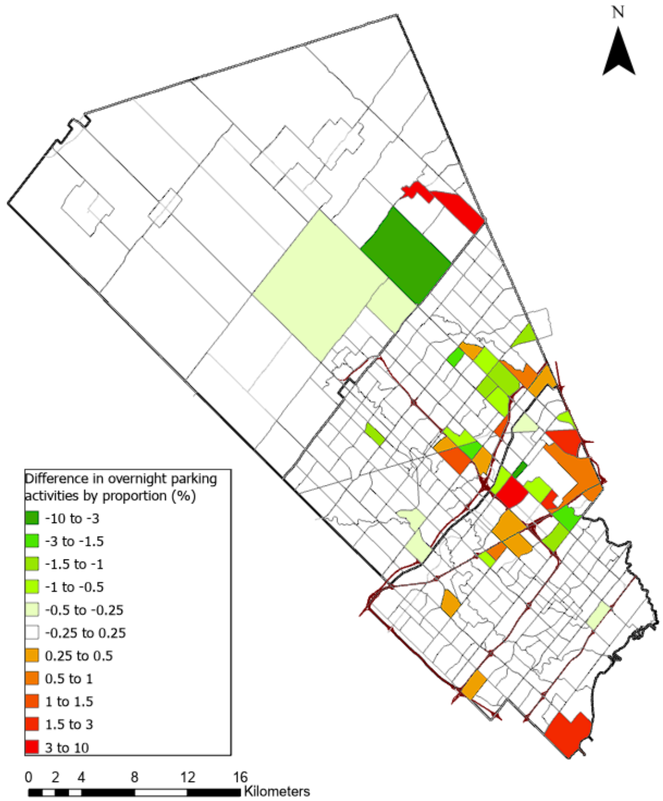


Figure 23 Difference in Overnight Parking Activity from 2019 to 2020

Subsequently, the overnight parking events are segmented based on their location type. The first category is firms that are primarily identified as rest areas for freight parking. Within the rest area categorization, the top firm possessed approximately 600 trips in 2019 out of 1,000 trips at all rest areas. Rest area locations with at least 50 overnight trips are denoted in this thesis as major rest areas (MRAs). This is based on applying an approximate 10% multiplier to 600 trips at the top MRA. The second category of overnight parking comprises the minor facilities not represented in further analysis. These include minor DCs and minor rest areas. The minor DCs are initially identified when determining the top 50 DCs within the region as the DCs outside the top 50 for each year. Overnight trips are identified through an eventual trip to a major DC, therefore these minor facilities may be included in the overnight trips as an eventual trip to a major DC. This category also includes rest areas that are not denoted earlier as MRAs in the first category.

The third category represents the remaining firms that possess overnight activity that are not identifiable as a rest area or distribution centre. Appendix B contains the breakdown of parking activities for the second and third categories at the TAZ level. The first category represents the MRAs that will be used in the optimization process and are identified below.

Figure 24 and Figure 25 present the MRA locations for further analysis in 2019 and 2020, respectively. The numbers within each figure correspond to the numbering of the firm in Table 8 below. These firms are presented with the Strategic Goods Movement Network shown in dark red. Figure 24 identifies five MRAs with at least 50 parking activities. Two areas are located in the area northeast of the interchange between Highway 401 and 410. One of these locations is a Flying J Centre at the southwest corner of Dixie and Britannia Roads. The other location is the Husky/ESSO in the southeast corner of the same intersection. This location provides ample space for truck parking compared to other stations or parking areas provided by ESSO. Another MRA in Mississauga is a Petro Pass Truck stop north of the Dixie Road and Derry Road intersection near the Brampton border. This location possesses less capacity compared to the previous two locations. Another ESSO gas station is north of Highway 407 by McVean Drive and Queen Street. This location is also near major freight areas in Vaughan outside the study area. Finally, a northern site is identified in Caledon near other freight-based firms on Centreville Creek Road between Healy Road and Mayfield Road.

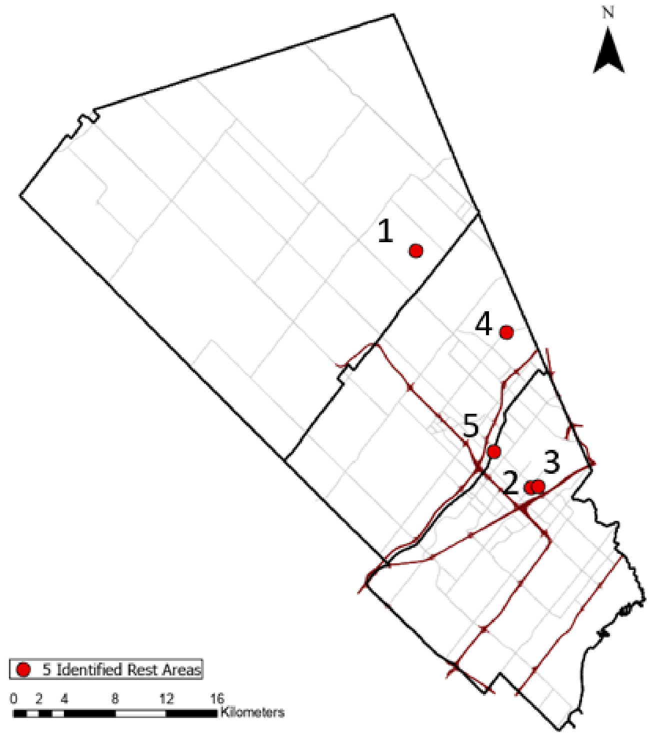


Figure 24 Five Rest Areas Identified – 2019

In Figure 25, eight MRAs are identified for 2020. However, the increased count of MRAs within this year is based on the increased size of the 2020 dataset since a count of 50 overnight trips was considered instead of a proportional value. An inset map is also presented for the Dixie and Britannia intersection to differentiate between the MRAs within the crossing. Four of the five locations from 2019 are included, while the ESSO station near McVean Drive and Queen Street is not included. This leaves an additional four locations. An unknown private facility located north of the Goreway Drive and Highway 407 interchange is identified as a parking location with overnight parking activity. Another rest area is identified immediately to the northeast of Pearson Airport as a general parking area used by private automobiles and freight. This location is north of the Airport Road interchange with Highway 409. Further analysis indicates that this location only serves one of the top 50 MDCs within the next day which may indicate a dedicated parking lot for that firm specifically, However, this location is retained due to meeting the required minimal number of stop events. Furthermore, two more locations are identified at Dixie Road and Britannia Road, with four total locations at that intersection. One location is a truck parking terminal provided by a shipping firm. It is unclear if this location is private or publicly accessible. This location is also adjacent to the Husky/ESSO previously identified at the same corner of the intersection. The final location in 2020 is another Petro Pass Truck Stop located northwest of the Dixie Road and Britannia Road intersection.

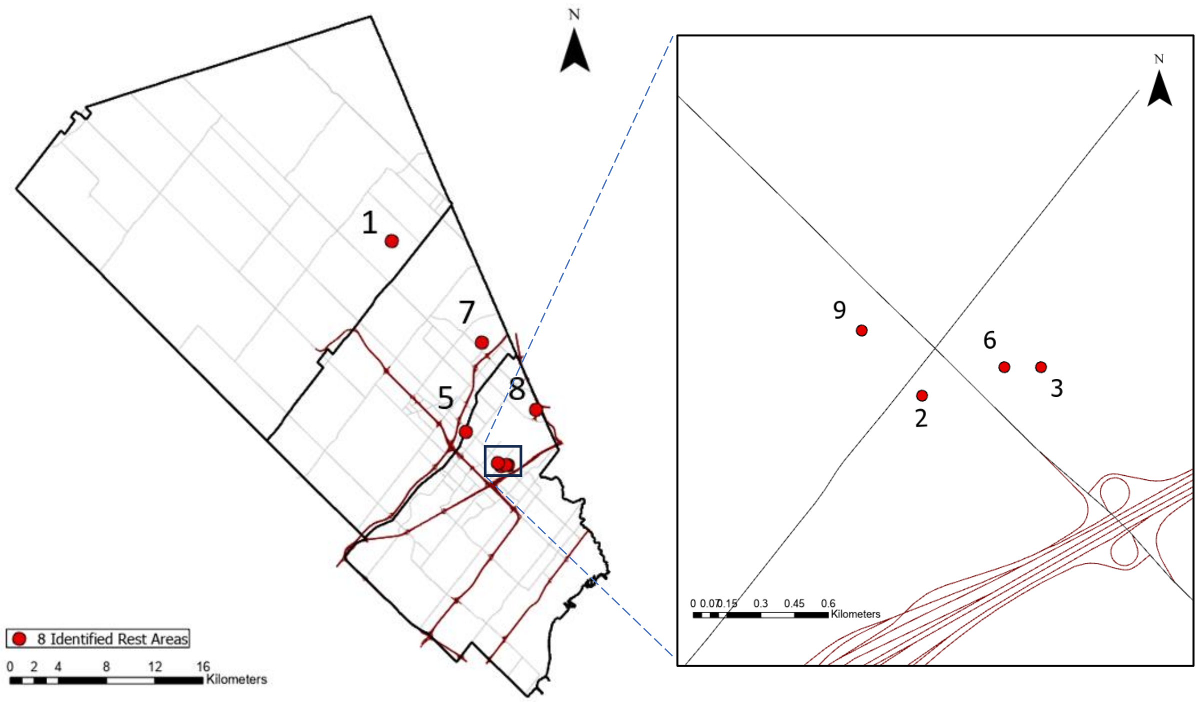


Figure 25 Eight Rest Areas Identified - 2020

Table 8 below presents the proportion of rest stops at each MRA as a proportion of the total overnight parking activities in the given year 2019 or 2020. Compared to the MDC analysis, the proportion of trips are presented at each location or parcel rather than the zone since the MRAs do not have a data restriction of privacy imposed on them. The table ranks 2019 MRAs in order of proportion first and then the non-mutual MRAs in 2020 in order of proportion. The differences between the two years at mutual rest stop facilities are identified. The Flying J Travel Centre represents a similar proportion of parking activity between the two years with about 2.75%. However, other locations possess differences between the two years. For the parking yard in Caledon, the location represented almost 9% of parking activity compared to only representing 2% of parking activity in 2020. This difference is seen in Figure 23 in the zone to the central-eastern Caledon showing a solid green colour due to a large reduction in parking activity from 2019 to 2020. In other words, a majority of the decrease in overnight parking at the TAZ level is attributed to the reduction in the 2020 data for this parking facility. A reduction in the proportion of overnight activity at the Husky/ESSO location is also noticeable, with the activity reduced by 50% from 2019 to 2020. The other mutual location is the Petro Pass Truck Stop at Dixie and Britannia, which also possesses a reduction but is not as consequential as the other variations.

Table 8 Percentage of Overnight Rest Stops at each Rest Facility

Facility	City	2019	2020
1 Caledon Parking Yard	Caledon	8.14%	1.58%
2 Flying J Travel Centre	Mississauga	2.75%	2.78%
3 Husky/ESSO at Dixie and Britannia	Mississauga	1.40%	0.60%
4 ESSO Station at McVean and Queen	Brampton	1.38%	N/A*
5 PetroPass Truck Stop at Dixie and Derry	Mississauga	0.85%	0.65%
6 Transport Terminal at Dixie and Britannia	Mississauga	N/A*	2.41%
7 Parking Area near Airport Road and Highway 409	Mississauga	N/A*	0.97%
8 Private Parking near Goreway and Highway 407	Brampton	N/A*	0.65%
9 PetroPass Stop at Dixie and Britannia	Mississauga	N/A*	0.46%

**The areas that are labelled N/A indicate that these locations are not included for further study. There is still potential overnight activity at these firms but below the benchmark value.*

5.6 Chapter Summary

Freight parking activity in the Region of Peel has changed over the two study years. One observation when examining the difference between the two years is the increased activity level within Caledon in the 2020 pandemic year compared to the 2019 pre-pandemic year. Differences are also observed where 9 out of the top 10 zones in 2019 have a reduced proportion of parking activity in the next year. In other words, the zones with the most activity have some of their activity distributed to other areas within the region. Land use also provides further context to the differences between the two years. However, industrial and commercial land use has remained consistent regarding freight parking between the two years. Reductions in parking activity proportions in offices and related land use like government use are observed due to pandemic restrictions. Within Caledon, there is also a noted higher proportion of freight parking activity within residential areas for both years.

The top 50 MDCs for both years are identified and attributed to their TAZs. As mentioned in the general trends for the region, firms in Caledon are more represented in 2020 compared to 2019. For both years, the top firms tend to surround the Pearson Airport and by Highway 401 and Highway 410 interchange. However, when examining these firms proportionally, the top 10 zones that possess the MDCs include an equivalent proportion of all parking activity between years, with about 60% of all MDC parking activity attributed to these top 10 zones. When examining Brampton and Mississauga, a similar trend is present where both cities have their top 10 zones representing an equivalent proportion of approximately 25% of all parking activity within each city. Brampton has a slightly increased proportion in 2020, with 30% of all parking activity within the city. When examining MDCs from a temporal scenario perspective, most scenarios do not exhibit many differences between the two options per each case. The largest difference in the comparison analysis is observed when comparing short-term and long-term parking in 2019, where the top 10 zones represent 66% for short-term parking and 77% for long-term parking.

The algorithm for overnight parking is applied to determine where parking activities occur before arriving at identified MDCs the next day. Five MRAs are identified for 2019 along with 8 rest areas identified for 2020. The MRAs observed a higher proportion of overnight activity in 2019 when compared to 2020, where the overnight activity is distributed over more firms. Differences in the overnight parking between the two years are dependent on specific firms as seen for the Caledon MRA where parking activity reduced from 8% of the 2019 overnight activity to 2% of the 2020 overnight parking activity even though parking activity as a proportion has increased for the town at whole, especially for MDCs.

CHAPTER 6: OPTIMIZATION OF PARKING FACILITIES

The locations discussed in Chapter 5 are used as inputs to model truck trips travelling from major rest areas (MRAs) to major distribution centres (MDCs) in the Region of Peel. The P-median model is selected for the optimization to select a subset of P rest area locations from among the candidate MRA locations, that are best located to efficiently serve trucks before their delivery. Constraining for a small set of locations is used here to represent a pandemic situation with limited resources where it may not be feasible for the public sector to ensure that there are appropriate supplies and facilities at all locations.

ArcGIS Network Analyst is used to determine travel times between two locations. A gravity model is calibrated to calculate a negative exponential factor representing the utility of travel time. Open Solver is used to run the optimization model and perform three scenarios. Scenario A is presented with the optimization of the overnight trips determined in Chapter 5.5. Scenario B uses all zones within the Region of Peel as candidate locations instead of the existing rest area locations from Scenario A. The results for the second scenario provide insights into the ideal locations for rest area facilities. Finally, Scenario C is presented to determine the ideal location to construct a new facility as an addition to the identified rest areas. This scenario therefore forces the solution to include a small set of existing MRAs while adding one new candidate location.

6.1 Input Parameters

6.1.1 Travel Time Impedance

The travel times between MRA and MDC sites are not readily available. Existing trip times from GPS-based data could be calculated but will only provide information on existing origin-destination (O-D) pairs. The proposed optimization seeks to analyze any potential O-D pairs including those found to exist in the GPS dataset as well as pairings that have not yet been observed. Therefore, the ArcGIS Network Analyst O-D Matrix tool is used to estimate travel times between the MRAs and MDCs for the 2020 and 2021 years. As the two years have different sets of MDCs and MRAs, the travel times are determined for both years. These travel times are obtained using 7 a.m. on Wednesday for 2019 and 6 a.m. on Thursday for 2020 due to these days and times being the most common hours that the overnight parking events ended for each year. These travel times are used as an input to determine gravity model parameters for travel time within this analysis. An alternative analysis can use free-flow travel times to capture the traffic conditions during the onset of the pandemic (Stone, 2020). Table 9 below displays the results of applying the negative potential gravity model equation presented in Equation 6 to determine the θ value to use in the P-median formulation in Equation 8. The 1,111 trips in 2019 and 1,655 trips in 2020 are used for each year, respectively. These are the trips travelling from the MRAs to MDCs for each year. The parameter $\propto$ is also presented in Table 9 but is not utilized in optimization.

Based on Table 9, the parameter θ for 2019 is 0.0211 but does not meet 95% confidence with an interval between -0.002 and 0.045. The parameter θ for the year 2020 is 0.029 with a 95% confidence interval between 0.015 and 0.043. Appendix C presents the factors from a day-of-week categorization to demonstrate how the factors change based on temporal and outlier categorization. The parameter will be used in the optimization to reflect the influence, or relative weight, of travel time for each O-D pair. The larger coefficient for 2020 implies a larger decrease in the travel time weight as the time between two locations is increased when compared with 2019.

Table 9 Regression Results to Determine Factor θ

Year	**Coefficient θ**	**t-stat**	**p-value**	**Coefficient α**	**t-stat**	**p-value**	**R^2**
2019	0.0211	1.78	0.08	0.4573	3.79	0.00	0.08
2020	0.0290	4.05	0.00	0.3809	4.91	0.00	0.08

6.1.2 Optimization Setup

Based on the overnight trip analysis in Chapter 5, five rest areas are identified in 2019 and eight rest areas are identified in 2020 as shown in Figure 24 and Figure 25. These facilities represent potential origins in the optimization. Furthermore, 43 of the 50 major distribution centres exhibited demand for overnight rest trips. The filtering process for distribution centres applies to both years, with each year containing some overlapping facilities and some unique facilities with 28 MDCs and 4 MRAs shared between both years.

The MDCs represent the destination of each trip to be optimized and these locations are fixed based on the determination of overnight trips. However, overnight night trip demand will not only be inclusive of trips from the MRAs. Alternative locations in which overnight parking activities occurred are included in the optimization. These include gas stations, truck repair, and rental shops with ten or more overnight trips. These other firms are not included as origin locations to be considered within optimization, but the trips from these locations will be included as demand to be optimized for each scenario. In total, 1707 trips are to be optimized in the year 2019, and 2669 trips are optimized in the year 2020. Travel times that represent part of the cost of this optimization process are calculated using the ArcGIS Network Analyst O-D trip allocation tool. The negative exponential model parameter for each year determined in the gravity model analysis above is used to weigh the travel time.

6.2 Results

There are three scenarios of optimization are defined within this analysis as noted in Chapter 4.5. Table 10 below summarizes the three scenarios within this analysis.

Table 10 Scenarios of Optimization

Scenarios	**Description**	**P Parameter Input**
Scenario A	Optimizing the available rest areas for trips destined for the MDCs which have exhibited demand for overnight parking. The P-median problem presents multiple solutions based on the number of rest areas open.	Cases of P equal to one to five, and P equal to one to eight, are conducted for 2019 and 2020, respectively.
Scenario B	The rest area locations are replaced by zones covering the region. The P-median problem is used to identify ideal zones for rest area facilities to serve MDCs that have exhibited demand for overnight parking. Only one rest area is allowed within a single TAZ to avoid redundancy.	Cases of P equal to 2, 6, and 10 zones are conducted for both 2019 and 2020.

Table 10 Scenarios of Optimization

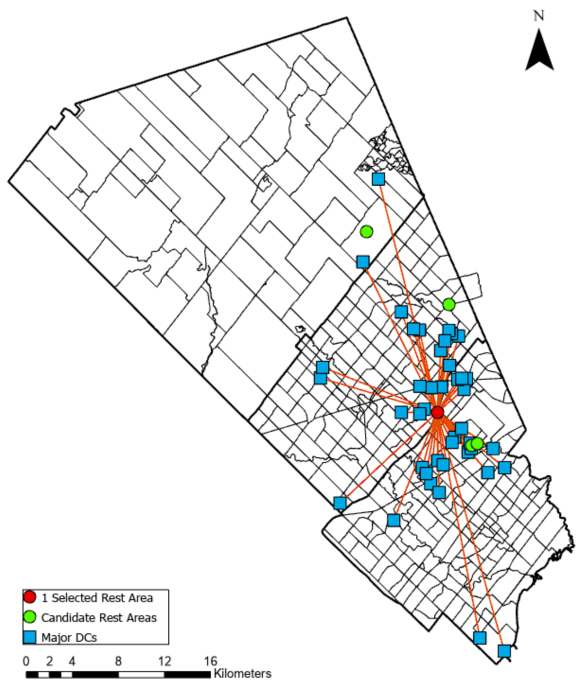
Scenario C	The zones containing existing MRAs in Scenario A are constrained to be open. The best location to construct a new rest area facility each year is optimized in relation to the existing rest areas.	For 2019, there are 5 MRAs in 5 zones, therefore the additional MRA is identified with P equal to 6. For 2020, there are 8 MRAs in 6 zones, therefore an additional MRA is determined with P equal to 7.

6.2.1 Scenario A

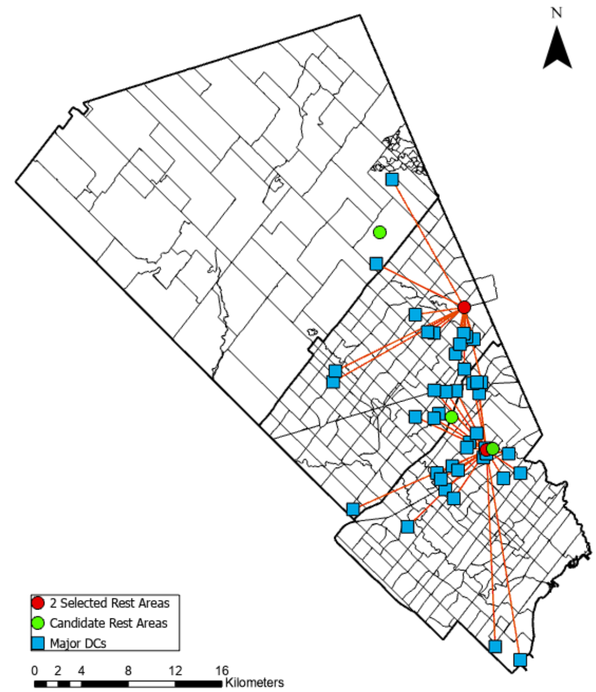
The first optimization scenario considers MRAs from Figure 24 and Figure 25 as potential origins for trips headed to the MDCs after staying at MRAs overnight. The following maps visually present the results as the input value for P is adjusted to change the number of available rest areas.

Figure 26 presents the optimized travel between the five MRAs and 43 MDCs for 2019. The nearest MRA origin for each MDC destination is shown in the maps using straight lines; however, each trip is calculated using congested travel times. In Figure 26a, the Petro Pass Truck Stop at Dixie and Derry is open to provide service to all distribution centres as the only MRA available. This facility is situated at a central point adjacent to the border between Mississauga and Brampton. In Figure 26b, the previously selected rest area is unselected, and instead, the Flying J Travel Centre and the ESSO station near McVean Drive and Queen St. are open. In this case, the Flying J Travel Centre is providing service to distribution centres in Mississauga and certain MDCs in southern Brampton while the ESSO station servicing nearby MDCs in eastern Brampton and serving the MDCs in Caledon.

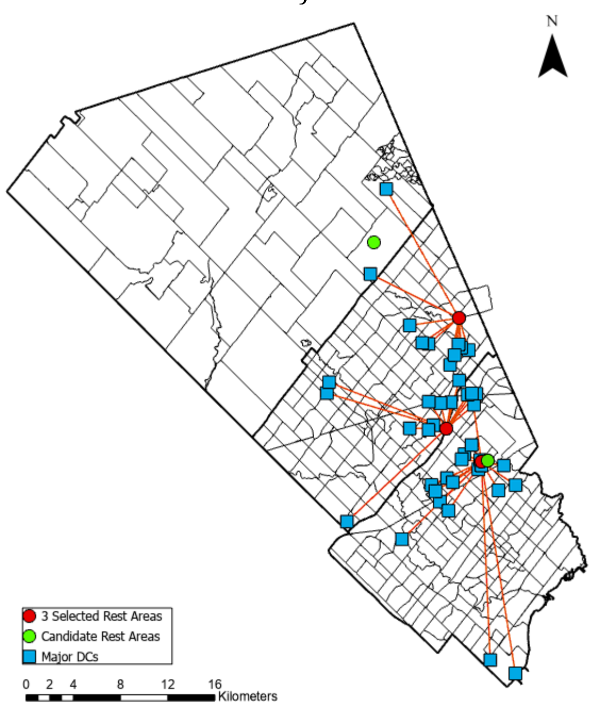
When opening three rest area facilities, other differences are examined. In Figure 26c, the initial rest area reopens to provide service to southern Brampton, with the Flying J Travel Centre continuing to serve the majority of MDCs in Mississauga. In Figure 26d, a Caledon parking facility is open and serves the two MDCs in the town. Finally, in Figure 26e, the Husky/ESSO is open near the Flying J Travel Centre, and it services the MDCs in the eastern and southern parts of Mississauga. In this case, Husky/ESSO is providing service to MDCs that was previously provided by the Flying J Travel Centre.



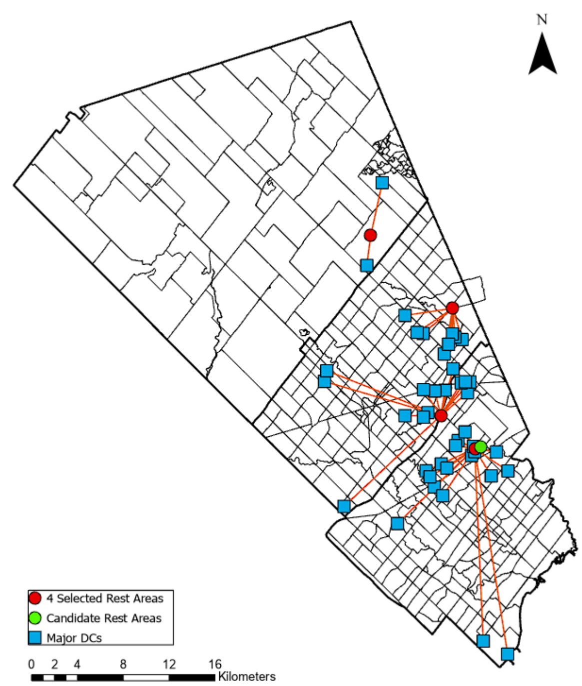
a)



b)

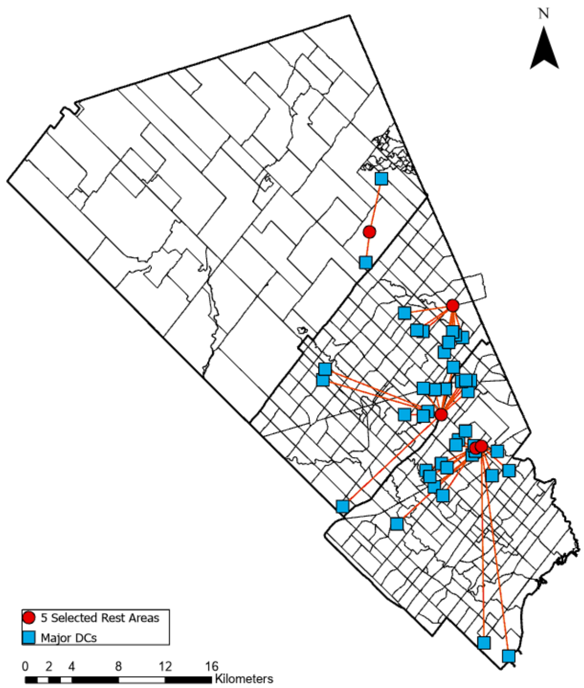


c)



d)

Figure 26 Scenario A Results - 2019



e)

Figure 26 Scenario A Results - 2019

Figure 27 presents the optimized travel between the eight identified rest areas and the 43 distribution centres for the year 2020. Travel from MRAs to MDCs improves when more rest areas are open, as shown by the shorter lines connecting locations. In Figure 27a, the first open rest area facility is the Husky/ESSO rest area in the southeast portion of the Dixie and Britannia intersection. When compared to 2019, this rest area serves the increased demand within Mississauga compared to the evenly split MDC demand between the two cities in the previous year. In Figure 27b, the private parking lot near Goreway Drive in Brampton provides service to MDCs within Brampton and Caledon and the Flying J Travel Centre has been selected to provide service in Mississauga. However, the Husky/ESSO is not open. This replacement indicates that the Husky/ESSO was previously selected due to shorter travel times towards MDCs in Brampton and Caledon, compared to the Flying J Travel Centre being closer to MDCs within Mississauga, even though both of these rest areas exist within the same intersection.

In Figure 27c, the Petro Pass at Derry and Dixie is open, providing service to MDCs in western and central Brampton on top of the service offered by the other rest areas selected in Figure 27b. Figure 27d, the MRA opening in northeast Mississauga by Airport Road, where it serves MDCs nearby and the MDCs in the southwestern portion of this city. The proximity of this rest area to highway infrastructure that borders the City of Toronto, Highway 427, allows it to have shorter travel times to the MDCs in the southwestern part of the city near the connected Queen Elizabeth Way. Figure 27e, the Caledon parking facility serves the MDCs in Caledon as the fifth open MRA. Figures 27f-h show the opening of the remaining three rest area facilities near Dixie and Britannia. Figure 28 is added below to provide a closer look at the changes in the optimization for the rest areas by the Dixie and Britannia intersection.

Based on Figure 28, the differences in the optimization as more rest areas are open in the Dixie and Britannia are observed. As mentioned, Figure 28a initially represents the opening of Husky/ESSO since it is the best location to provide service to all MDCs within the region if only one rest area could be open compared to the Flying J Centre being open when two MRAs are open in Figure 28b. Figure 28c shows the case in which six rest areas are open where the Petro Pass MRA services just one MDC. Figure 28d shows the reopening of the Husky/ESSO in the southwest corner of the intersection. Finally, Figure 28e provides the same O-D assignment as seven open rest areas since the opening of the shipping company's parking terminal did not have any additional performance to the previous number of rest areas open. In other words, the proximity of this facility to the nearby Husky/ESSO renders the parking terminal facility redundant within this analysis. However, the redundancy of this facility is based on this analysis not considering supply. If capacity could be considered, there is a possibility that the parking terminal facility is a needed facility to meet the demand while ensuring that the MRAs are not over capacity.

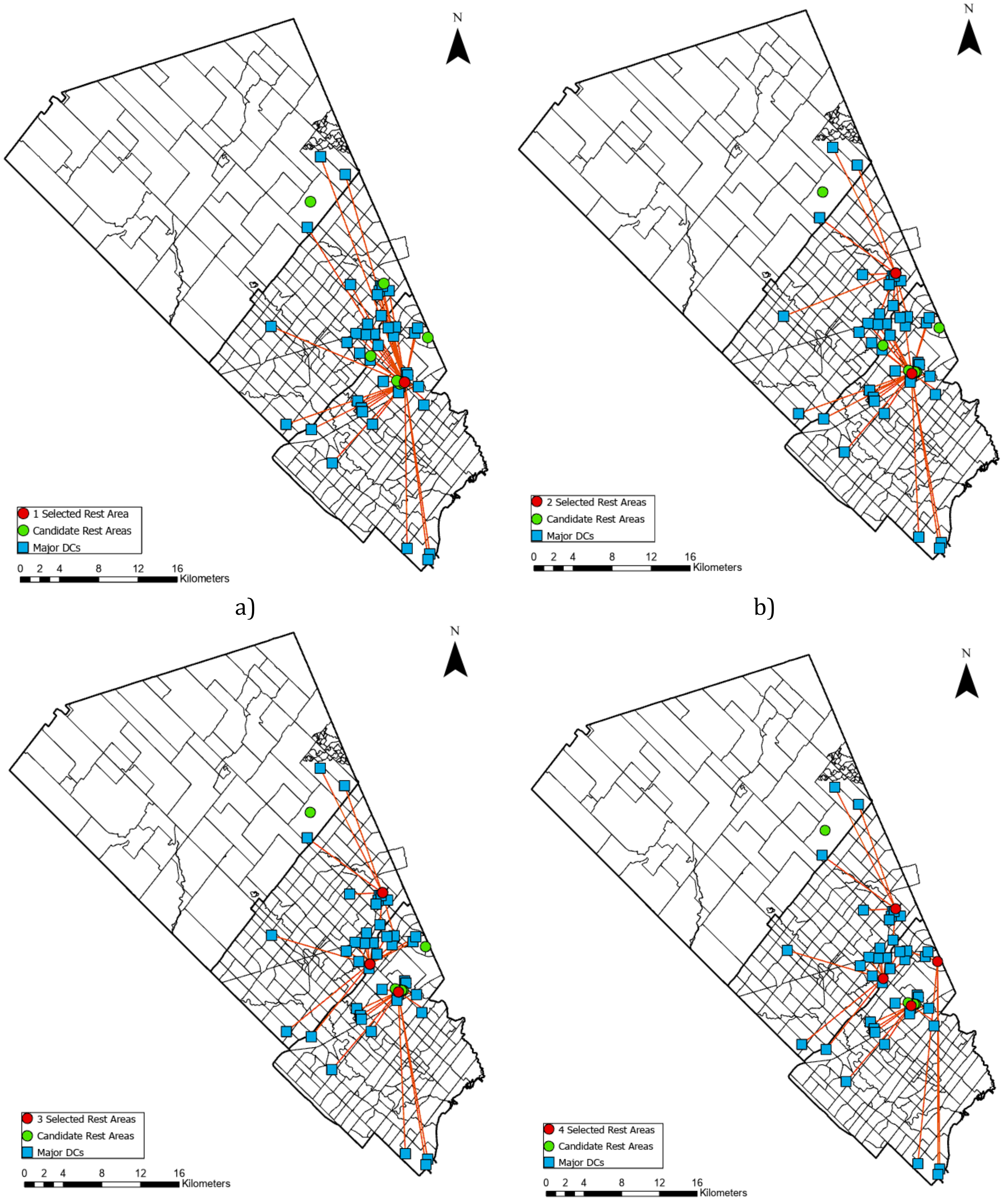
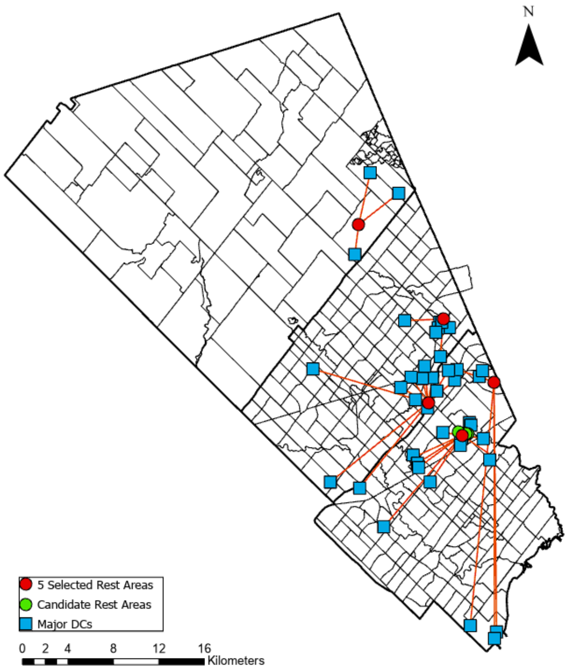
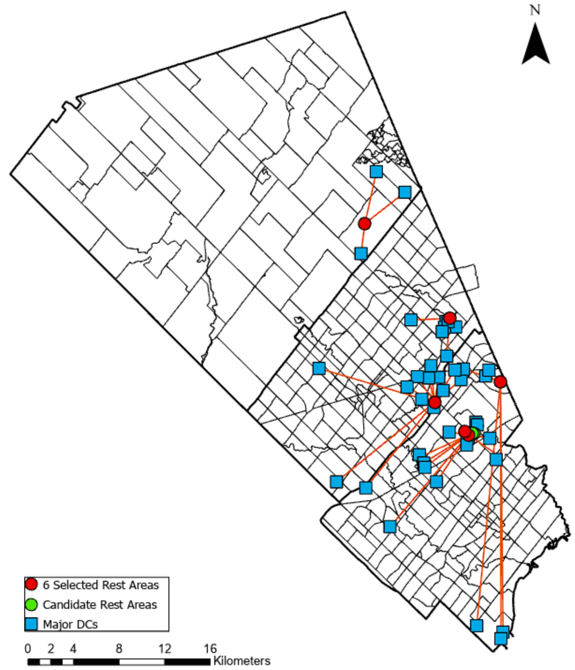


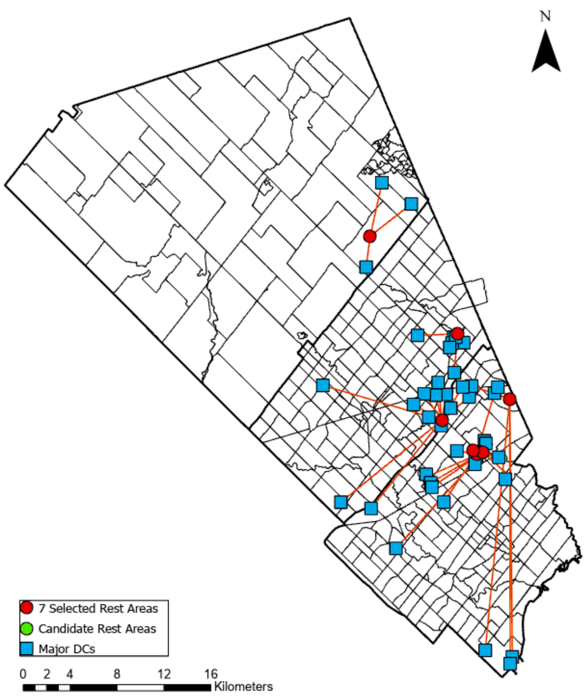
Figure 27 Scenario A Results - 2020



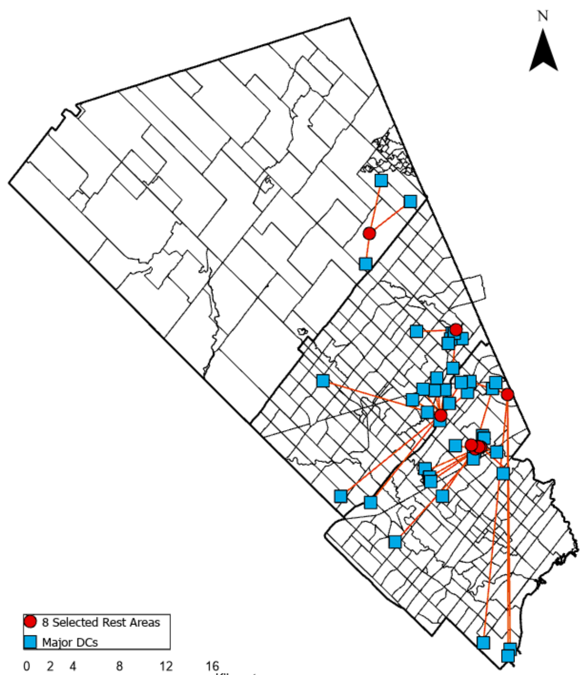
e)



f)



g)



h)

Figure 27 Scenario A Results - 2020

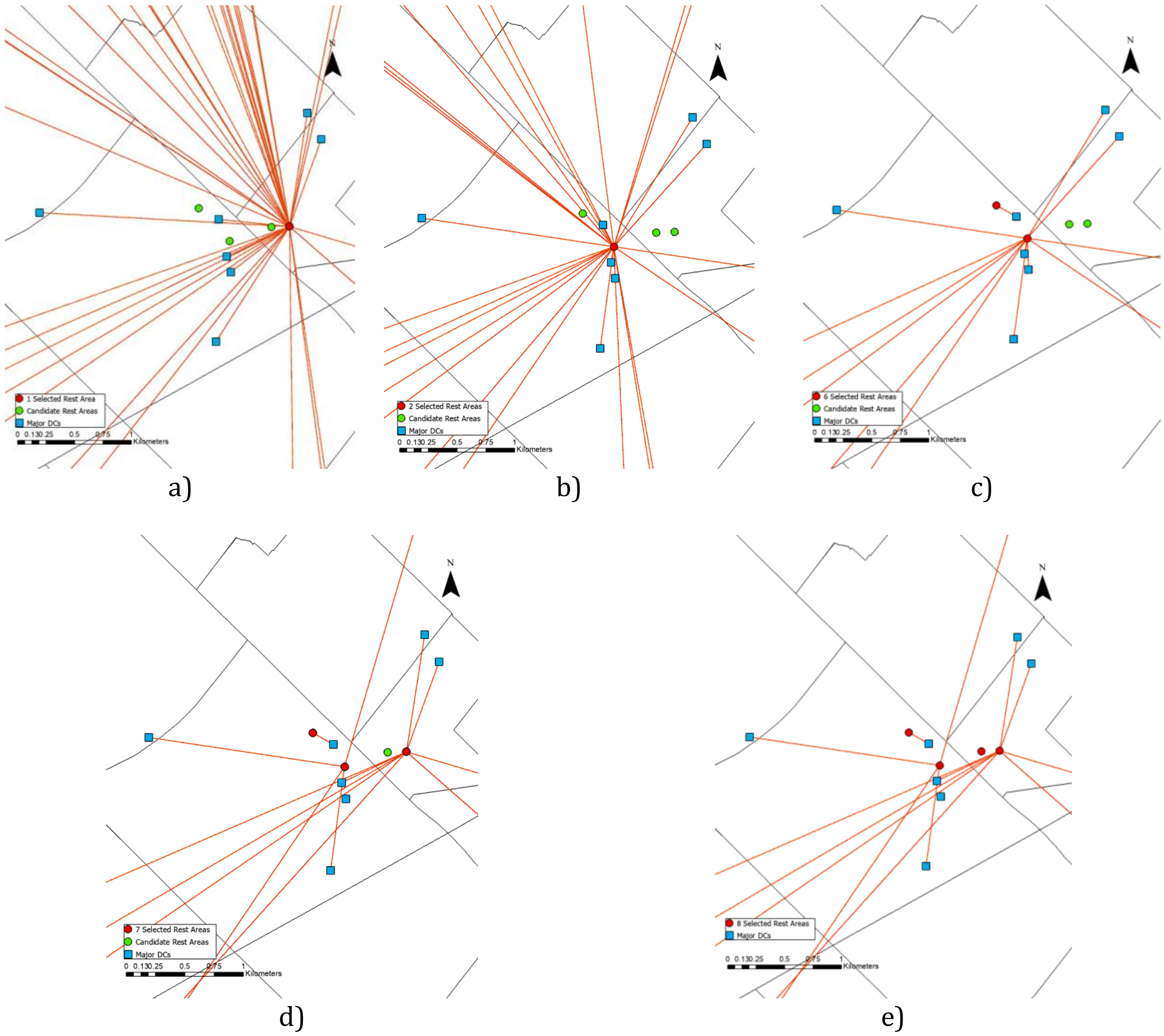


Figure 28 Scenario A Results at Dixie and Britannia - 2020

Table 11 presents the optimization results for the year 2019 based on the objective function and aggregate travel time measures. A diminishing return for the objective function is observed with a larger number of open MRAs. The average travel time was reduced by approximately 23% from one open MRA compared to three open MRAs. However, comparing three open MRAs to five open MRAs, the average travel time only reduces by approximately 4%. Furthermore, the maximum travel time for this year only marginally changes from one open facility to two open facilities and then minimally changes as more rest areas are open.

Table 11 Scenario A Travel Time Results - 2019

Number of Open Rest Areas	Objective value	Average travel time (mins)	Maximum travel time (mins)
1	412.99	13.45	31.33
2	351.13	11.20	28.78
3	326.25	10.31	28.78
4	317.11	9.96	28.78
5	315.98	9.92	28.60

Table 12 below presents the results for the year 2020. The change in travel time starts to diminish when more than two rest areas are open. From one rest area to three rest areas, the average travel time decreases by approximately 25%. However, from three rest areas to eight rest areas, the average travel time only reduces by approximately 9%. There is no change between the opening of seven and eight rest areas. The eighth rest area is redundant and has no travel associated, as shown in Figure 28e. The maximum travel time also reduces by 10% from one rest area facility to four open facilities but does not change with more open MRAs.

Table 12 Scenario A Travel Time Results - 2020

Number of Open Rest Areas	Objective value	Average travel time (mins)	Maximum travel time (mins)
1	737.29	11.49	28.77
2	613.37	9.33	26.23
3	574.41	8.67	26.23
4	554.30	8.34	25.94
5	535.24	7.96	25.94
6	533.82	7.94	25.94
7	532.41	7.92	25.94
8	532.41	7.92	25.94

The distribution of trips based on travel time is also presented to examine how the optimized travel varies per time increment in minutes. This distribution is presented in a line graph format comparing travel times to the percentage of trips at or under the travel time within the result. This result is shown cumulatively so that a better result will have more trips at lower travel times or a horizontal shift of the function towards lower travel times.

Figure 29 and Table 13 below present the cumulative distribution of trips per travel time for 2019. Opening more rest area facilities allows more trips to be completed in less time. At 10 minutes, 20% of trips are at or under this travel time with one MRA compared to 53.5% of trips with two open MRAs and 65% of trips with three to five open MRAs. In contrast at 20 minutes, 90.5% of trips are at or under this travel time with one MRA open, 94% of trips with two MRAs open and 98% of trips with three to five MRAs open. In other words, when opening two MRAs, the time savings are higher compared to opening three or more MRAs. From a minute-to-minute perspective, there is little difference between opening 3 to 5 MRAs in 2019.

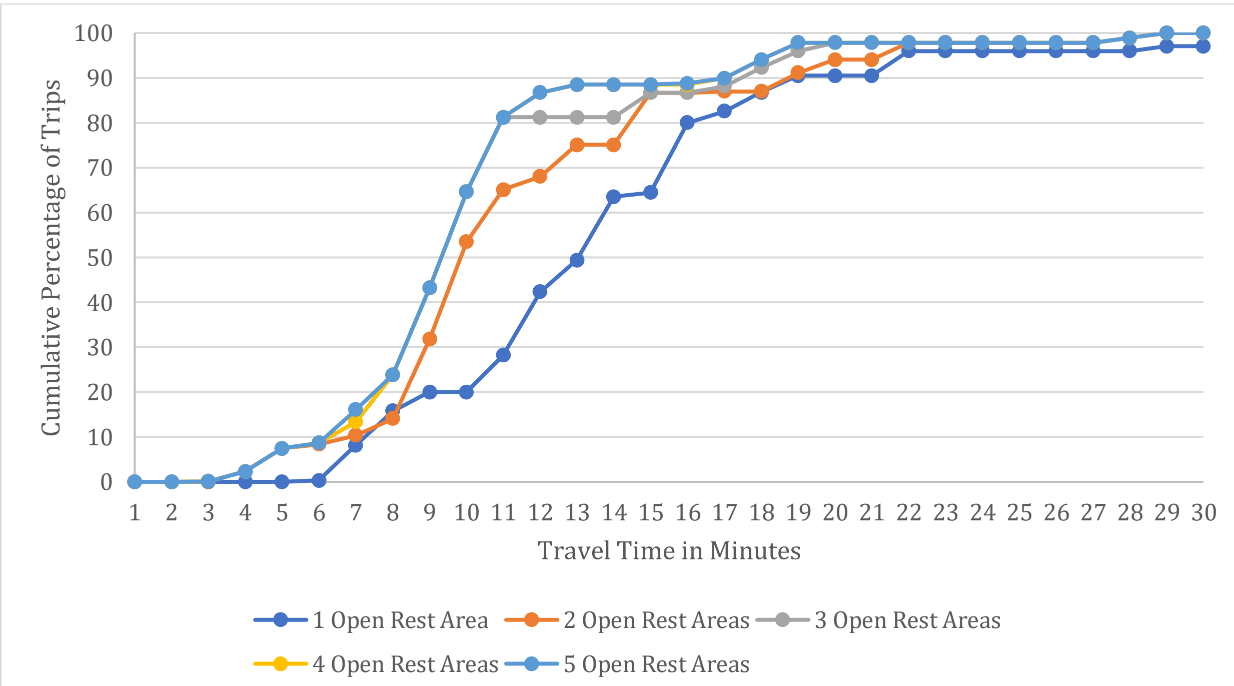


Figure 29 Scenario A Cumulative Distribution of Trips by Time – 2019

Table 13 Scenario A Cumulative Distribution of Trips by Time - 2019

P	5 mins (%)	10 mins (%)	15 mins (%)	20 mins (%)	25 mins (%)	30 mins (%)
1	0	20.04	64.44	90.51	96.02	97.07
2	7.44	53.49	86.70	94.08	97.83	100
3	7.44	64.62	86.70	97.83	97.83	100
4	7.44	64.62	88.52	97.83	97.83	100
5	7.44	64.62	88.52	97.83	97.83	100

Figure 30 and Table 13 below presents the cumulative distribution of trips per travel time for 2020. Similar benefits are seen where two open MRAs show better incremental performance compared to the opening of the remaining three to eight MRAs. At 10 minutes, 43% of trips are at or under this travel time with one open MRA compared to 72% of trips with two open MRAs and 84%

of trips with 3 to 8 open MRAs. In contrast at 20 minutes, 94% of trips are at or under this travel time with one MRA open, 95% of trips with two to four MRAs open and 97% of trips with five to eight open MRAs. Moreover, the distribution of trips is identical for every case of open areas from five to eight, due to the redundancy of the MRAs within the Dixie and Britannia intersection having minimal travel time changes between them.

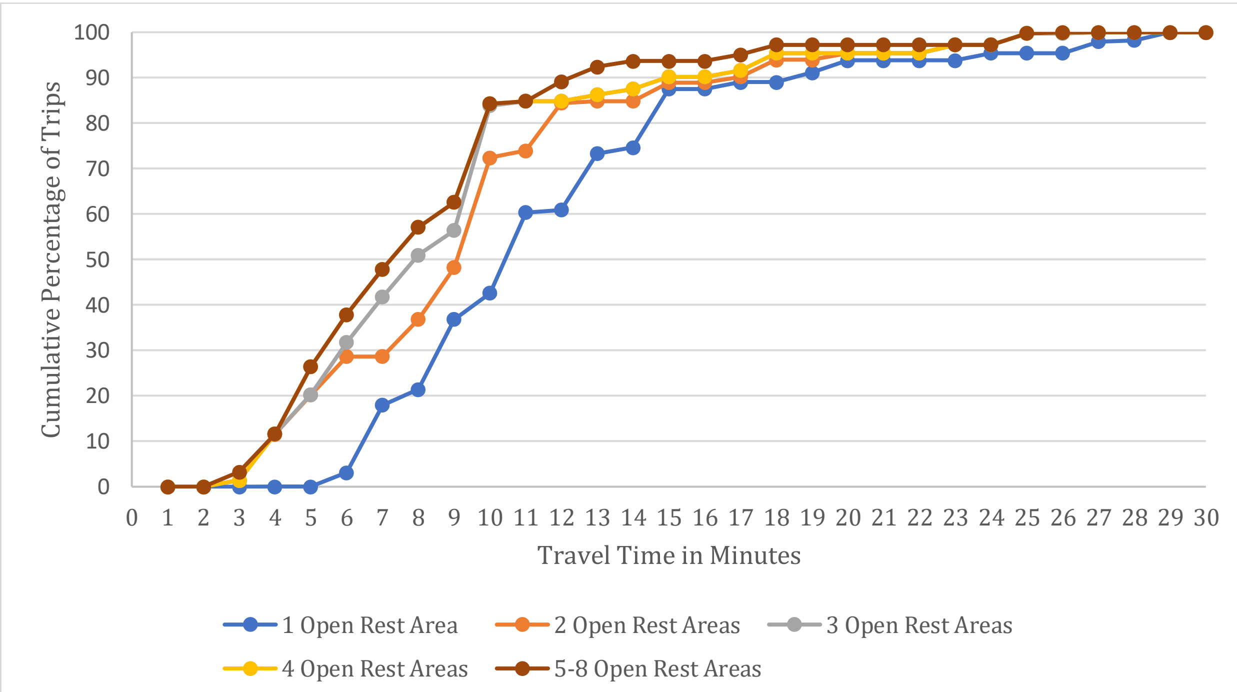


Figure 30 Scenario A Cumulative Distribution of Trips by Time – 2020

Table 14 Scenario A Cumulative Distribution of Trips by Time – 2020

P	5 mins (%)	10 mins (%)	15 mins (%)	20 mins (%)	25 mins (%)	30 mins (%)
1	0.04	42.64	87.52	93.78	95.43	100
2	20.23	72.39	88.95	95.43	99.78	100
3	20.27	83.89	90.18	95.43	99.78	100
4	26.41	84.26	90.18	95.43	99.78	100
5	26.41	84.26	93.63	97.23	99.78	100
6	26.41	84.26	93.63	97.23	99.78	100
7	26.41	84.26	93.63	97.23	99.78	100
8	26.41	84.26	93.63	97.23	99.78	100

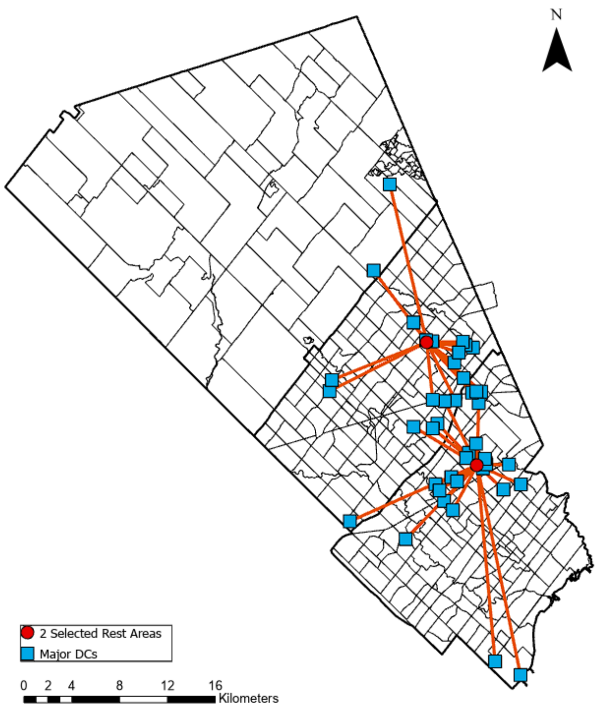
6.2.2 Scenario B

The candidate MRA locations for Scenario B are represented as centroids of the traffic analysis zones (TAZ). It is assumed that no existing rest areas are available. Instead, MRAs are placed in the optimal zone locations as the P parameter is incrementally increased.

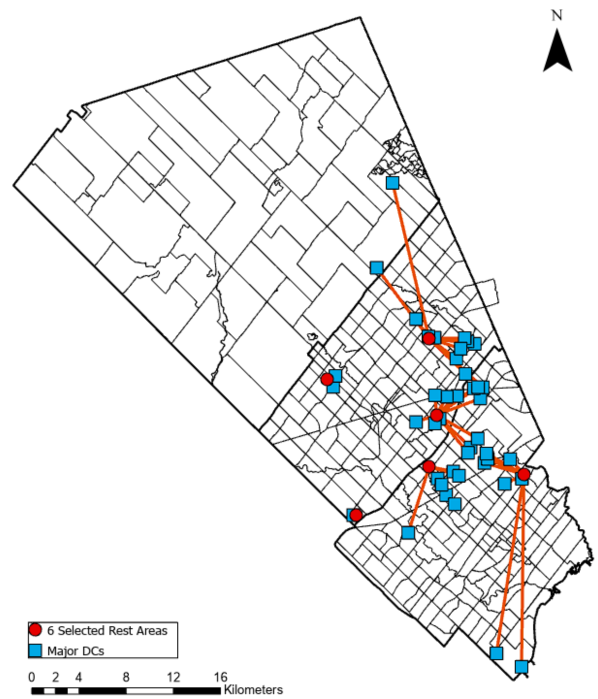
Figure 31 presents the optimized results when two, six, and ten rest areas are located to serve the 43 distribution centres for the 2019 year. In Figure 31a, two open rest area facilities are present, one in Mississauga in the same zone as the Flying J Travel Centre and another in central-east Brampton. The Mississauga rest area serves all MDCs in the city and four MDCs in Brampton near the municipal border. The other rest area serves the remaining MDCs in Brampton and Caledon. With the limited number of open facilities, the MDCs are limited to be serviced by the closest facilities, but a considerable distance is still observed for more remote MDCs in the west. More MRAs need to be open to provide a smaller time of travel for MDCs that are within the western portion of the region.

In Figure 31b, visual improvement is observed with five additional facilities providing service to MDCs immediately adjacent to the facility. Two rest area facilities are open in new areas within Mississauga that serve the many MDCs in the northeastern part of the city. Within Brampton, the remaining 4 open MRAs are in each corner of the city with the northeastern MRA servicing the MDCs in Caledon. The eastern MRAs in Brampton provide service to more MDCs compared to the west there are more MDCs in the east. This is in contrast to Scenario A, where MRAs are exclusive to the eastern portion of the city.

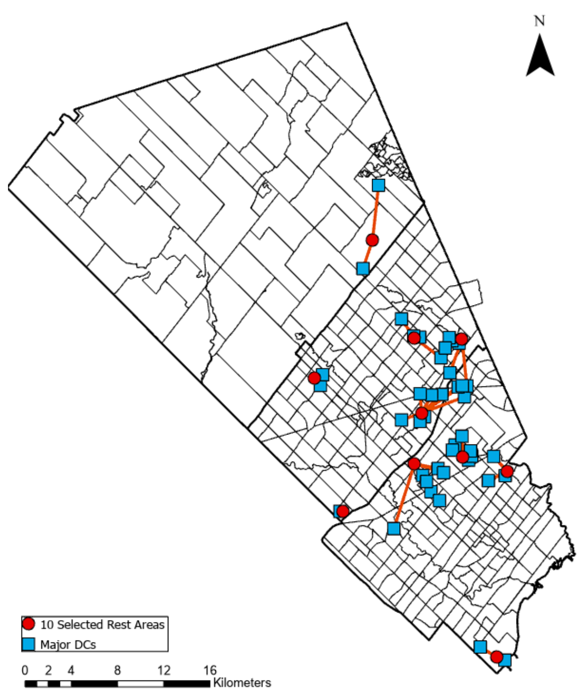
In Figure 31c, these facilities serve MDCs nearby in localized groups. In Mississauga, four open facilities serve groups of MDCs in the city's northwestern, southwestern, eastern and north-central areas. The MDCs to the north of the airport but within Mississauga are served by one of three facilities in eastern Brampton. The remaining two facilities within Brampton are in the western portion of the city and serve remote locations in that area. The final rest area facility in the case is within Caledon, serving the two MDCs within the town. In other words, opening ten facilities within this scenario has allowed for each MDCs to be serviced MRA that is close in distance.



a)



b)



c)

Figure 31 Scenario B Results – 2019

Figure 32 presents the optimized results for the 43 distribution centres in the 2020 year. Figure 32a shows two rest area facilities in similar locations to the prior year with similar assigned MDCs to the corresponding facilities. However, the rest area within Mississauga also serves MDCs in western Brampton. The rest area within Mississauga is closer to Highway 410, allowing it to serve a nearby MDC. Similar to the previous year, the MDCs in the western part of the region have long travel times from MRAs being selected in the eastern zones of the region.

Figure 32b shows differences from the previous year with six open MRAs. The main differences are the MRA in western Mississauga serving MDCs in the western part of the region, an MRA in Caledon servicing the 3 MDCs in the town, and MDCs in Brampton being served by an additional MRA in northeastern Mississauga. In contrast to Scenario A, the MRAs selected by the zones are similar in location to the identified MRAs in Scenario A. Service by a MRA for MDCs in the western part of the region is the main difference.

Finally, in Figure 32c with ten facilities open, the additional four MRAs serve, but the locations still differ from the prior year. In Mississauga, there are now six open facilities this year compared to only three in the previous year due to the increased number of MDCs within Mississauga. Along with an MRA in the city's southwestern corner, five additional rest areas go along the border with Brampton and serve MDCs within Mississauga and southern Brampton. Four MRAs within Brampton serve the eastern part of the city and one MRA in Caledon services three MDCs in the town again. Therefore, the main benefit of opening MRAs within any zone in the region is to provide service to the MDCs in the western part to reduce travel time to remote MDCs.

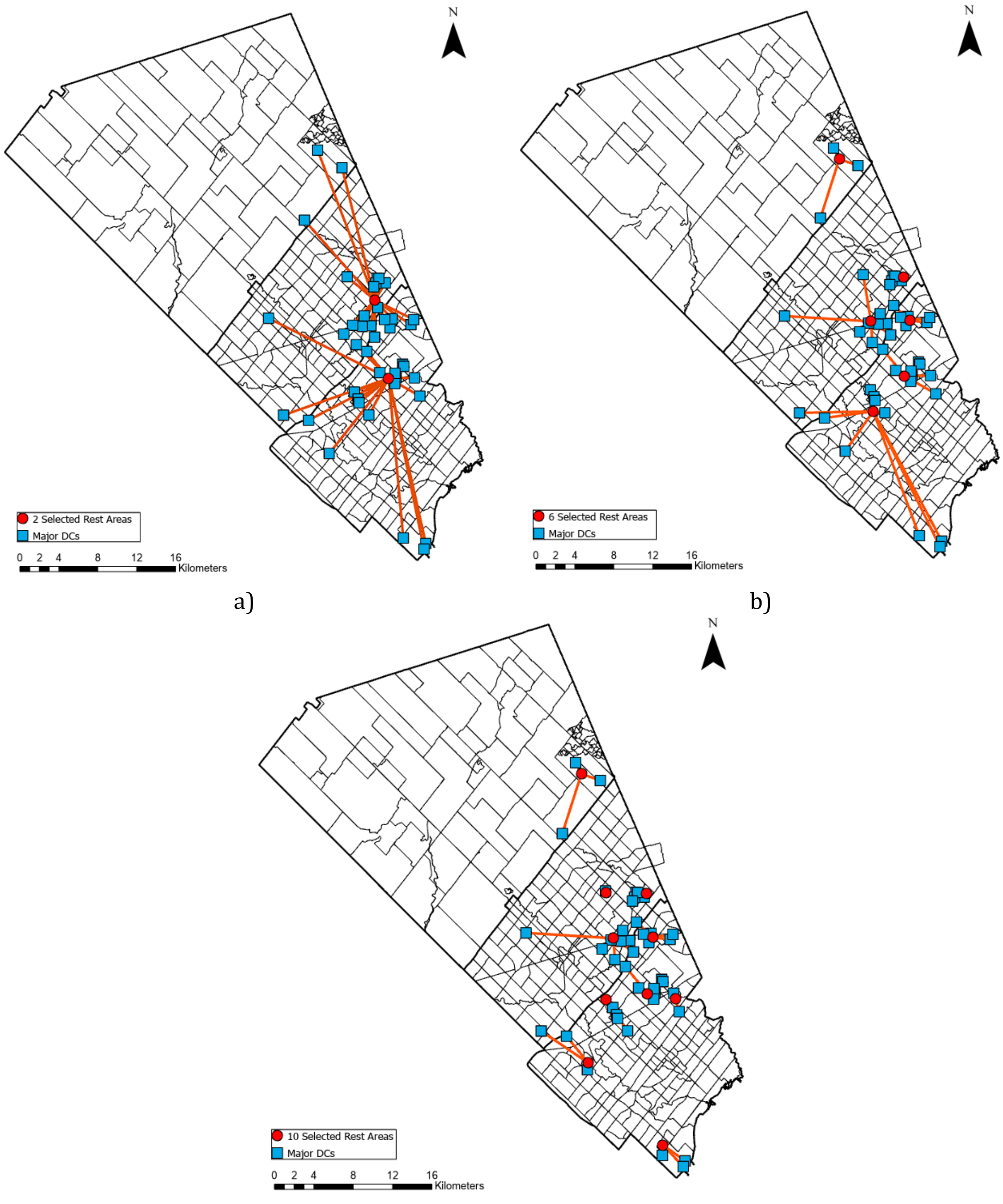


Figure 32 Scenario B Results – 2020

Table 15 presents the optimization results for the year 2019. The average travel time is reduced by approximately 33% from two rest areas to six rest areas and by approximately 18% from six rest areas to ten rest areas. Compared to Scenario A with existing MRA facilities, increased travel time savings are present when more open rest area facilities. Furthermore, the maximum travel time is reduced by approximately 15% from two rest areas to six rest areas and by approximately 49% from six rest areas to ten rest areas. Servicing distribution centres in the region's western part have aided in achieving this reduction.

Table 15 Scenario B Travel Time Results - 2019

Number of Open Rest Areas	**Objective value**	**Average travel time (mins)**	**Maximum travel time (mins)**
2	227.97	8.66	23.54
6	191.93	5.81	19.90
10	159.28	4.74	10.13

Table 16 below presents the optimization metrics for the year 2020. The average travel time is reduced by approximately 29% for two open MRAs compared to six open MRAs and by approximately 18% for six open MRAs compared to ten open MRAs. A reduction is observed in the maximum travel time between each increment of rest areas. In 2020, the maximum travel time is reduced by approximately 16% from two open rest areas to six rest areas and by approximately 25% from six to ten rest areas. The performance in terms of maximum travel time is reduced this year due to the long distances between origins and destinations from a central Brampton rest area travelling to a western MDC presented in Figure 32c. Compared to 2019, this year has a higher maximum travel time at two open rest facilities, which is also evident in Figure 32a, due to more western MDCs present within this year.

Table 16 Scenario B Travel Time Results - 2020

Number of Open Rest Areas	**Objective value**	**Average travel time (mins)**	**Maximum travel time (mins)**
2	545.54	8.22	23.35
6	405.66	5.86	19.52
10	339.93	4.79	14.57

Figure 33 and Table 17 presents the cumulative distribution of trips per travel time in Scenario B for 2019. Compared to Scenario A, the changes in the distribution of trips have shifted from occurring in 10-20 minutes area to 5-10 minutes. In this case, the comparison is observed at 5 and 10 minutes. At 5 minutes, 24% of trips are equal to or under the travel time with two MRAs, 54% of trips are equal to or under the travel time with six MRAs, and 67% of trips are at or under the travel time with ten MRAs. At 10 minutes, it is 75%, 90% and 99% respectively. In Scenario A, 5 minutes of travel only possessed at most 8% of trips and 10 minutes of travel ranged in 20-66% as presented in Table 13. In other words, the vast majority of trips are completed in all scenarios equal to 10 minutes or under.

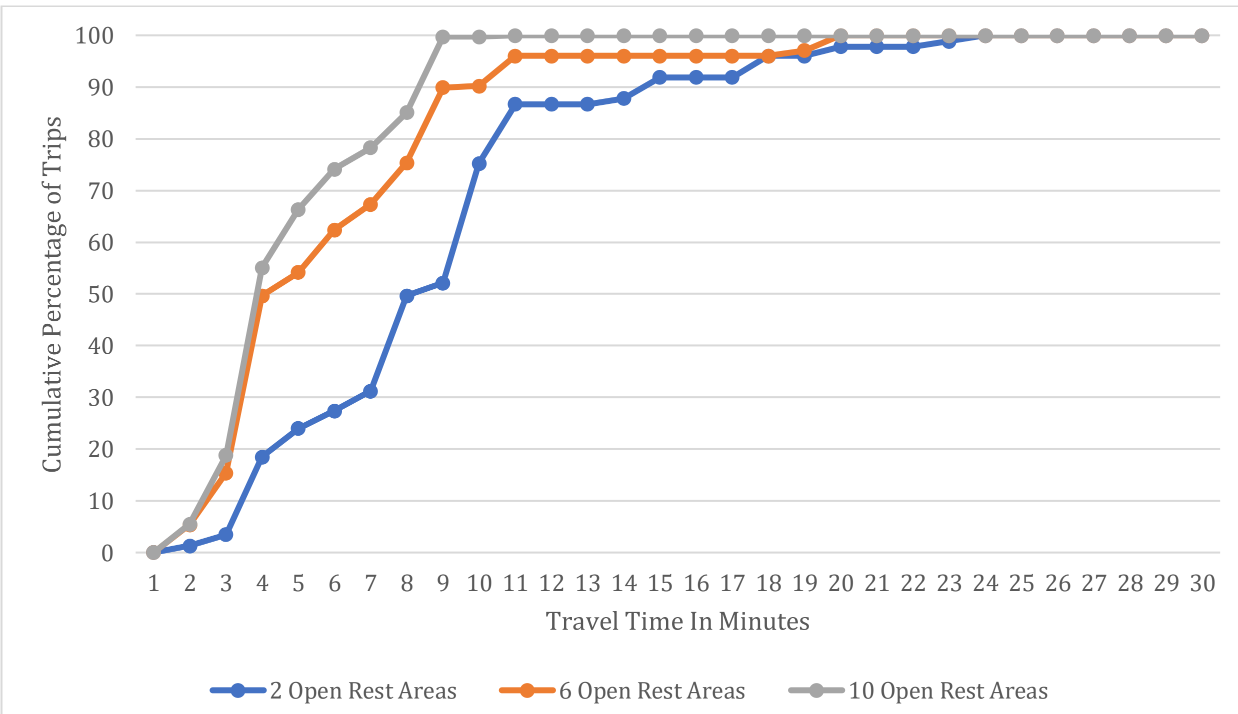


Figure 33 Scenario B Cumulative Distribution of Trips by Time - 2019

Table 17 Percentage of Trips per Travel Time Increment for Scenario B - 2019

P	**5 mins (%)**	**10 mins (%)**	**15 mins (%)**	**20 mins (%)**	**25 mins (%)**	**30 mins (%)**
2	23.96	75.22	91.86	97.83	100	100
6	54.19	90.22	96.02	100	100	100
10	66.62	99.71	100	100	100	100

Figure 34 and Table 18 presents the cumulative distribution of trips per travel time in Scenario B for 2020. Similar to 2019, most of the trips are occurring between 5 to 10 minutes. At 5 minutes, 19% of trips are at under the travel time with two MRAs, 53.5% of trips are at under the travel time with six MRAs, and 60% of trips are at or under the travel time with ten MRAs. At 10 minutes, it is 77%, 86% and 95% respectively. When compared to the previous year, more trips are more than 20 minutes with 10% of trips above this threshold compared to 3% with two open MRAs. However, this is still an improvement to Scenario A where 5 minutes of travel only possessed at most 26% of trips and 10 minutes of travel ranged from 42 to 85% as presented in Table 18. In other words, although more trips are travelling at higher travel times this year, the usage of any zone within the region leads to lower travel times overall compared to Scenario A.

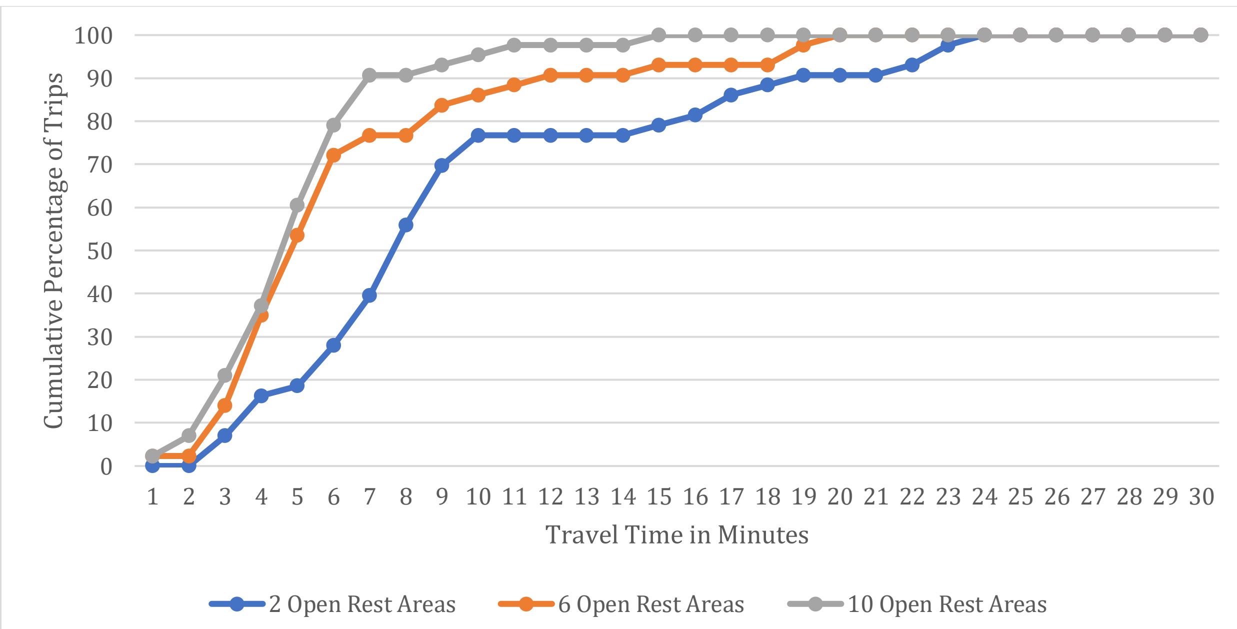


Figure 34 Scenario B Cumulative Distribution of Trips by Time – 2020

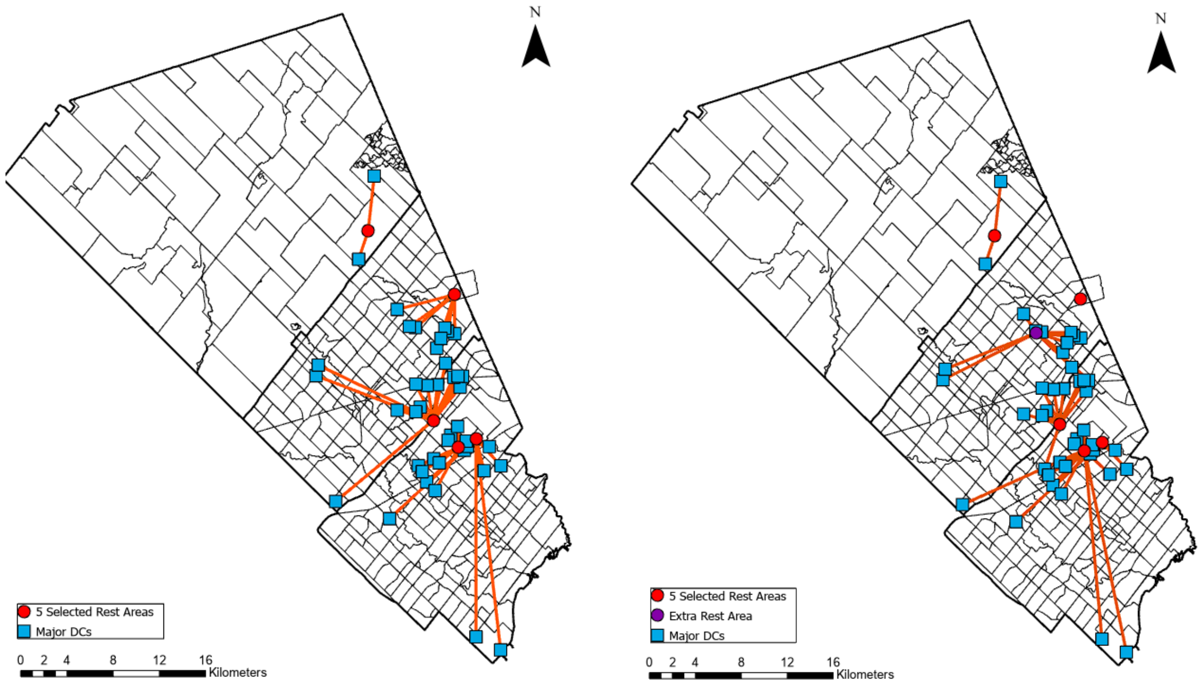
Table 18 Percentage of Trips per Travel Time Increment for Scenario B - 2020

P	5 mins (%)	10 mins (%)	15 mins (%)	20 mins (%)	25 mins (%)	30 mins (%)
2	18.60	76.74	79.07	90.70	100	100
6	53.49	86.05	93.02	100	100	100
10	60.47	95.35	100	100	100	100

6.2.3 Scenario C

Using the P-median optimization process, an additional rest area is determined as the ideal location to serve the demand for rest facilities in the region. This process incrementally adds the number of identified rest areas by one. The MRAs are associated with their corresponding zones. The coordinates for these locations are at the centroid of the zone, similar to Scenario B. In 2020, the eight rest areas were joined with six zones since there were two pairs of MRAs within the same TAZ. Therefore, the P parameter in this analysis for 2019 is six, and for 2020 is seven.

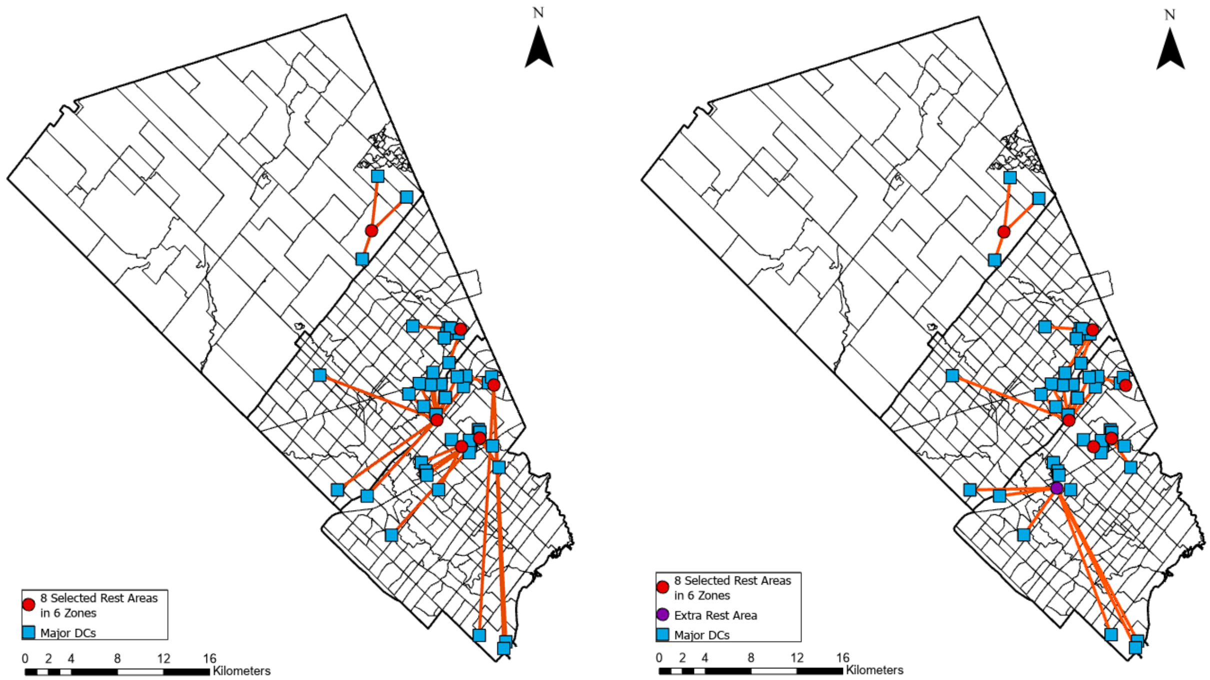
Figure 35 below the location of the additional rest area for the year 2019. Figure 35a first presents the five selected rest areas shown in Figure 26. However, these locations are presented within the centroids of their zones. Figure 35b illustrates the output of determining an extra rest area within the region on top of the current status quo identified in Figure 35a. The additional rest area is proposed to be located in central east Brampton and serve MDCs within eastern Brampton. Notably, this new facility replaces the service provided by the McVean Drive and Queen Street rest area. In other words, this optimization scenario proposes a replacement rest area instead of an additional rest area. It is essential to note that the intersection of McVean Drive and Queen Street is near a major freight location in the City of Vaughan, but trips associated with this area are outside the scope of this study.



a) b)

Figure 35 Scenario C Results- 2019

Figure 36 below the location of the additional rest area for the year 2020. In 2020, the eight existing rest areas are attributed to six TAZs. An additional rest area is identified in western Mississauga to serve distribution centres in the western part of the city and one additional DC in southwestern Brampton as presented in Figure 36b. This new facility is also evident in Scenario B when six and open ten rest areas, as illustrated in Figure 32b to Figure 32c. In this case, there is no replacement of existing facilities presented from Scenario A compared to the prior year. However, it is essential to note that the four facilities by Dixie and Britannia are associated with two zones, so redundancy may still exist with this intersection.



a) b)

Figure 36 Scenario C Results - 2020

Table 19 below presents the optimization metrics for the year 2019. In the year 2019, the average travel time reduces by 22%, and the maximum travel time reduces by 18% with the opening of the newly identified rest area facility. In other words, compared to Scenario A, more performance is presented from an incremental facility opening due to the choice of selecting an MRA to serve MDCs that are at a long travel time from the existing infrastructure.

Table 19 Scenario C Travel Time Results – 2019

Case	Objective value	Average travel time (mins)	Maximum travel time (mins)
8 Existing MRAs	532.41	7.92	25.94
1 Additional Rest Area	431.81	6.25	19.52

Table 20 below presents the optimization metrics for the year 2020. In 2020, adding a new rest area to the status quo has led to a 21% reduction in average travel time and a 25% reduction in maximum travel time. An increased performance is observed within this year due to the MRA being located in the western part of the region which is distinct from the eastern locations of the existing infrastructure. There is diminishing performance in the previous year due to the proposed facility replacing a selected facility compared to opening a new location.

Table 20 Scenario C Travel Time Results – 2020

Case	Objective value	Average travel time (mins)	Maximum travel time (mins)
8 Existing MRAs	532.41	7.92	25.94
1 Additional Rest Area	431.81	6.25	19.52

Figure 37 and Table 21 presents the cumulative distribution of trips per travel time for 2019. The main performance is seen at the 5-minute benchmark where 24% of trips are now at or under this travel time compared to only 7% with the existing MRAs. At 10 minutes, this performance is similar with 88.5% of trips with the additional MRA compared to 65% with the existing infrastructure. There is a diminishing rate in performance after 12 minutes where the distributions are similar to each other.

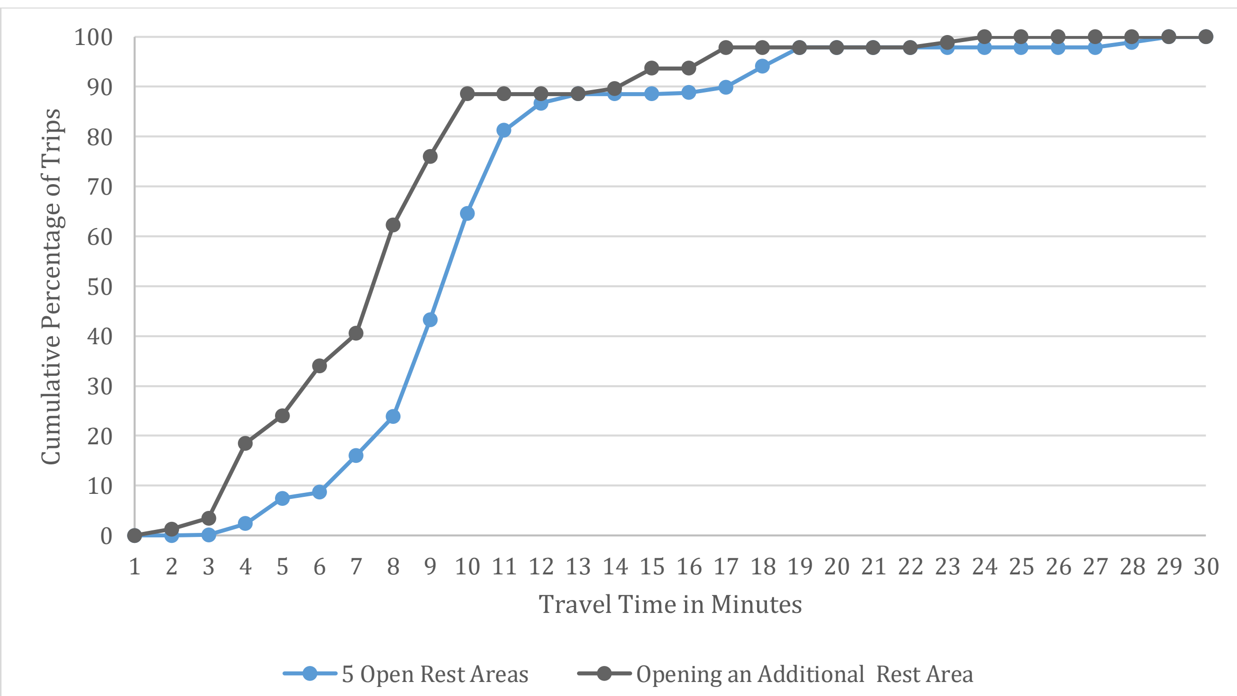


Figure 37 Cumulative Distribution of Trips for Scenario C – 2019

Table 21 Percentage of Trips per Travel Time Increment for Scenario C - 2019

P	5 mins (%)	10 mins (%)	15 mins (%)	20 mins (%)	25 mins (%)	30 mins (%)
5	7.44	64.62	88.52	97.83	97.83	100
6	24.02	88.52	93.67	97.83	100	100

Figure 38 and Table 22 below present the cumulative distribution of trips per travel time for 2020. The performance for additional MRA in this year compared to 2019 has diminished performance. This diminished performance is due to the 8 existing MRAs providing better service to the MDCs with 26% of trips at 5 minutes or under compared to 5 existing MRAs in 2019 with 7% of trips at 5 minutes or under. As such, the additional MRA is providing service to MDCs in the west that mainly reduces the maximum travel time. This reduction is presented when observing the 100% percentile occurring between 25 and 30 minutes for the existing infrastructure compared to 15 to 20 minutes with the new MRA.

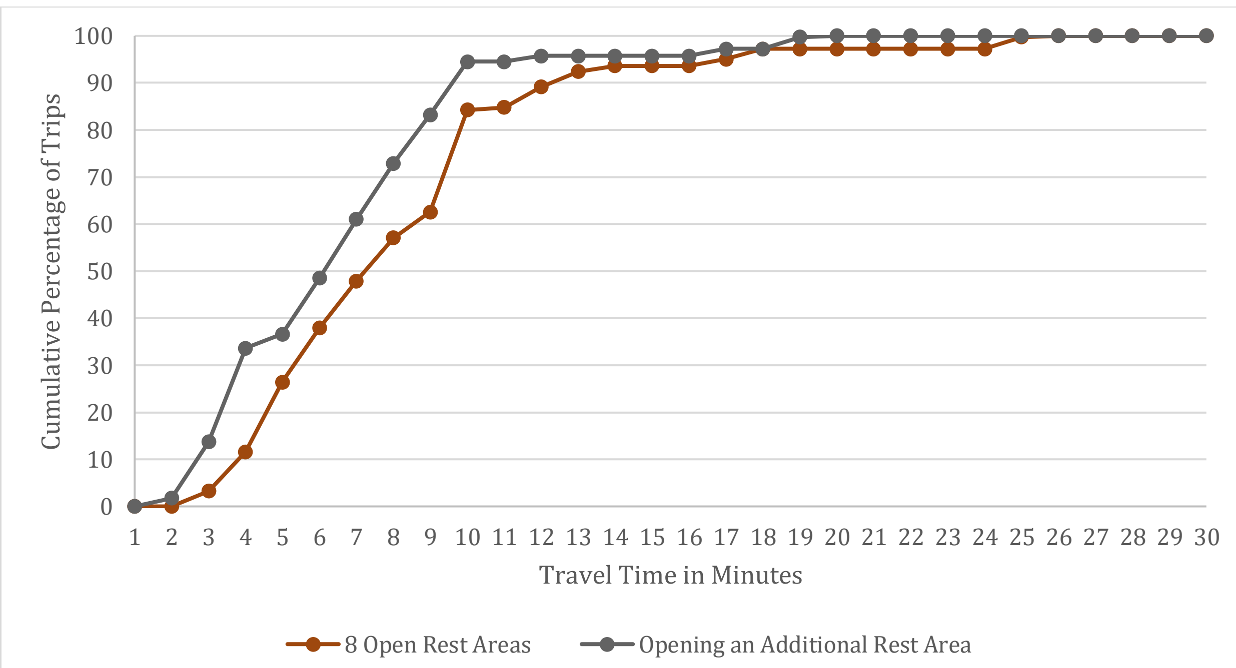


Figure 38 Cumulative Distribution of Trips for Scenario C – 2020

Table 22 Percentage of Trips per Travel Time Increment for Scenario C - 2020

P	5 mins (%)	10 mins (%)	15 mins (%)	20 mins (%)	25 mins (%)	30 mins (%)
6	26.41	84.26	93.63	97.23	99.78	100
7	36.61	94.53	95.77	100	100	100

6.3 Chapter Summary

The optimization in this chapter analyzes the ideal organization of trips between major rest areas (MRA) and major distribution centres (MDCs) based on the limited availability of the former sites.

The P-Median model is used to conduct this analysis. The first scenario optimizes the opening of existing MRA facilities. Within this analysis, a diminishing rate of return in the performance of opening incremental facilities is observed. This limited performance is observed when opening four to five MRAs in 2019 and five to eight MRAs in 2020 due to redundancy in the Dixie and Britannia intersection. Furthermore, the maximum travel times are only reduced by 10% overall for both years with no improvement in this performance metric after opening more than two in 2019 and four in 2020.

The second scenario used zones as potential locations for MRA facilities. The flexibility of opening rest areas in any area within the region provides increased performance as more rest areas are open. MDCs that are more remote are served through nearby MRAs to serve these locations. As such, both the. average and the maximum travel sees improvements in both years as the number of rest areas is increased from two to ten open facilities. The average travel time sees a diminishing rate of return, but the maximum travel time sees an increase in performance when going from six MRAs to ten MRAs due to the four remaining MRAs specifically providing service to MDCs with long travel times.

The final scenario in this analysis is the opening of an extra rest area facility in addition to the existing facilities from Scenario A. The existing MRAs are now represented by the TAZ zones using the centroid coordinates. The location of the additional facility is identified by determining the next zone within the region through an increment within the P-Median model. Within this case, the performance is mainly seen in the improvement in the maximum travel time since adding a new facility aims to provide service to MDCs who have long travel times with existing MRAs. The maximum travel time is reduced by 18% in 2019 and 25% in 2020.

CHAPTER 7: CONCLUSION

In the Region of Peel, a significant Canadian freight hub, the pandemic has had a profound impact on truck drivers. Rest areas are essential facilities for truckers, providing rest and necessary amenities during their work. Travel from these facilities to distribution centres is central to this thesis. GPS data is first used to determine where truck parking is occurring within the region. The data is also used to help identify major distribution centres (MDCs) and major rest areas (MRAs). A P-median problem is devised to optimize travel from MRAs to MDCs based on a limited number of available MRA locations adjusted by the P parameter. This scenario is used to reflect the limited resources available during a pandemic situation. The model is subsequently used to determine the ideal locations for MRAs by considering all potential locations in the study area using a set of zones. Finally, a third scenario is enacted to consider the best location for a new MRA when placed alongside pre-existing MRA facilities. For these analyses, both the pandemic year of 2020 and the pre-pandemic year of 2019 are examined to determine differences in the patterns of travel within the region.

7.1 Summary and Discussion

In this section, a summary of each analysis is presented to emphasize key takeaways.

Locations of major rest areas and major distribution centres

The first process in this study was to find methods to identify major freight facilities within the Region of Peel. To identify the sites, various data sources are used to provide an initial list of sites for both rest areas and distribution centres. One example is using literature that provides an explicit list of these firms. Another source utilizes DMTI points with SIC codes that match for both types of facilities. A dataset that explicitly identified firms is also used with Nevland's set for rest areas. After identifying these firms, the locations of the facilities are located at zones that surround the Pearson Airport in northeastern Mississauga and southeastern Brampton. However, a limited number of firms also exist within the western areas of the region and a limited number of firms in southeastern

Caledon. In other words, the Region of Peel possesses distinct areas in which freight facilities are mainly located without a uniform distribution in where they are placed.

On-street parking restrictions

The work provides a data-driven analysis of parking activities based on ATRI GPS datasets. Parking stops on the roadways are evident in major roadways throughout the Region and include streets adjacent to freight-related firms. Restricted access to these firms may lead to truck drivers using these roadways as alternative parking which is also unauthorized. This parking indicates the need for accessible rest areas that can provide valid alternatives for parking.

Land use trends

Land use represents a method of identifying zones with a common type of usage. Specific uses related to freight activity that are of interest include commercial, industrial and office-based use. Commercial and industrial land use still possess similar levels of activity between both years. The proportion of parking activity, as observed using the same GPS data, for office use has decreased by 50% during the pandemic for Mississauga and Brampton and by 90% in Caledon. On the other hand, parking activity has increased in the proportion of parking for vacant lots, but that may be attributed to the changes in land use year to year since the land use designation is based on the pre-pandemic year of 2019. In other words, parking activity in vacant lots in 2020 may be due to new developments in these areas where parking would not occur in 2019. For both years, low-density residential use in Caledon possesses parking activity at 2% of the total parking activity for the town. In comparison, the other two cities possess parking activity at 0.2% for that land use. Residential lots within Caledon are usually larger in which some lots are used for truck storage. However, this can also be attributed to unauthorized parking in these residential areas. In general, Caledon has distinct trends for land use compared to the other two municipalities. However, it is important to note that the datasets between the two years consist of different participant trucks which may influence results.

Temporal trends from 2019 to 2020

MDCs are ranked based on parking activities within their sites. Specific trends are observed when comparing the pandemic and non-pandemic years. In particular, MDCs within Caledon are more represented in the 2020 pandemic year compared to the 2019 pre-pandemic year. The proportional shift to Caledon may be due to higher density in the two larger cities. Truck drivers may focus their stops on areas that pose less risk of potential infection. Provided lists of MDCs are used to generate parking activity events from GPS data for in/out deliveries of goods movements. Appropriate mobility interventions such as temporary parking permission in private areas can be used to relieve demand during a pandemic.

Date and time-based filters are applied to understand how activities connected to MDCs vary based on temporal conditions. When looking at short-term vs long-term parking, the main difference is observed in the quantity of parking where the top zones possessed more long-term parking at MDCs. For example, in 2019, the top 10 zones possessed 66% of the parking for short-term parking while long-term parking possessed 77%. When examining the time of day, certain firms may have a preference to operate in the morning compared to the afternoon. For example, a zone in southwestern Mississauga possesses MDCs that are active in the morning as a top ten zone but have a smaller proportion of activity in the evening. Comparing weekends and weekdays presents spatial changes due to the closure of firms on weekends, particularly on Sundays. Furthermore, both years have the top 10 zones possess a larger proportion of activity on Sundays when compared to Thursdays. These temporal differences indicate that a scenario-based approach to implementing countermeasures may be helpful. As an example, reorienting the further analysis based on trips for Sunday can provide an alternative result to the prioritization of firms. However, the focus should be on days that exhibit the most demand for MDC parking which is Thursday for both years.

Overnight parking at major rest areas

Areas with significant truck parking are identified as MRAs for the optimization analysis of trucks that rest overnight before proceeding to their destination at an MDC. Parking activities in the overnight period are of interest due to the lack of supply of rest area parking spots within this period. These trips are used to identify MRAs that are used for subsequent travel to MDCs. Five MRAs were identified in 2019 compared to the eight considered for 2020 but this is due to a strict count of events of 50 events instead of a proportion-based benchmark. Furthermore, these MRAs are noted to be used mainly by long-haul freight vehicles and ArcGIS Network Analyst is used to determine the travel times from these facilities to MDCs. The demand for travel by distribution centres can factor into this travel time. The gravity model provides a tool in which regression is applied to determine these factors. These factors are then used for further analysis to account for a non-linear relationship between travel time and demand. The higher value of the factor obtained for 2020 indicates that trips between MRAs and MDCs are sensitive to travel times compared to 2019. In other words, it is observed that longer travel times between two locations indicated a lower likelihood of trips occurring between the two locations and that is more apparent within the pandemic year.

Scenario A results

The P-median optimization is used to vary the number of rest areas available for trucks starting a trip after overnight rest at an MRA. The first scenario determines the best existing MRA locations to keep open in the event of a pandemic with limited resources and further pairs the nearest available MRA to each MDC. In this analysis, a pronounced diminishing rate of return in the average travel time within this network is observed as more open rest areas. Furthermore, the maximum travel time within the analysis does not improve due to the existing rest areas being located in the eastern part of the region leading to large travel times to the western part of the region. The distribution of trips per travel time showed that travel patterns are identical between the cases after opening two MRAs in 2019 and three MRAs in 2020. This result suggests that scarce resources can be effectively deployed to a limited number of sites as long as they have sufficient capacity.

Scenario B results

The second scenario identifies optimal locations from among a comprehensive set of zones covering the Region of Peel. Cases of two, six, and ten sites are tested in this analysis. When examining the performance of the network by comparing two and six open MRAs, both average and maximum travel time improve with a reduction in the network. In 2019, the average travel time is reduced by 33% and the maximum travel time is reduced by 15% compared to 29% and 16%, respectively in 2020. In other words, the performance of the average travel time is higher than the maximum travel time. However, when further increasing the number of MRAs from six to ten, the benefits between the two metrics have different observations. The average travel time is reduced by 18% for both years. However, the maximum travel time by 49% and 25% for 2019 and 2020, respectively. In other words, the incremental addition of MRAs between a count of six and ten mainly added MRAs to zones adjacent to remote MDCs that reduced the longest travel times.

When comparing this to Scenario A where MRAs are at fixed locations with no improvement in maximum travel time, the usage of any zone for an MRA shows that there may be gaps in access for MRAs in each case. Within 2019, two MRAs in Scenario A has an average travel time of 11 minutes and a maximum travel time of 28 minutes. Scenario B for the same number of MRAs has an average travel time of 9 minutes and a maximum travel time of 24 minutes. The improvement in Scenario B is due to the opening of MRAs in the zones west of the existing MRAs chosen in Scenario A. Spatially, the difference is consistent in 2020 as well, where the MRAs in Scenario B are a few zones west of the zones representing existing MRAs in Scenario A. In Scenario A, the average travel time is 9 minutes, and the maximum travel time is 26 minutes. Scenario B has an average travel time of 8 minutes and 23 minutes. The same applies to 6 MRAs where Scenario A has a maximum travel time of 26 minutes and the maximum travel time is 19.5 minutes for the year 2020 provided by an MRA in Scenario B which is located in central-west Mississauga. In other words, when comparing the same number of MRAs between Scenario A and B, the improvement is mainly seen in maximum travel time due to the locations of the MRAs being located west of the existing ones.

Scenario C results

Finally, the third scenario determines the best zone in the Region of Peel to construct a new rest facility alongside the currently available MRAs. In 2019, the analysis resulted in one MRA opening in eastern Brampton. For this year, this new MRA replaces the existing MRA in eastern Brampton since the network completely disregards the preexisting MRA for the new one a few kilometres away. As such, the average travel time reduces by 22% and the maximum reduces by 18%. However, in 2020, a new MRA is constructed just west of the central zones in Mississauga and a reduction is observed by 21% and 25% for average and maximum travel time respectively. The zone proposed in 2020 for new construction is similar to the central-west zone presented in 6 open MRAs for Scenario B. This new zone serves the remote MDCs in western Mississauga and reduces travel time to these firms but there is a lower reduction in average travel time due to smaller demand from these remote MDCs. In other words, the benefit of adding MRAs to the network is mainly seen in improving maximum travel time but limited demand for these trips reduces the performance in maximum time.

7.2 Limitations of Research

The above analyses provide a method to use GPS data to observe trends in freight parking activity. However, the data represents only a sample of the total truck parking activities in the Region of Peel. Only a subset of trucks using communication vendors associated with the dataset are included. The companies and trucks in the dataset may change from year to year.

The analysis of stop events is based on a limited count of truck stops based on the spatial and temporal filters applied to a limited number of stops at the property level. For example, the least active firm used as an MRA only had a few dozen overnight truck stops with a connected trip to a nearby MDC. With the same context, the capacity of MRAs can also be accurately considered in the analysis as a constraint to how the network is presented. The current approach of this thesis applies a sample of the data to determine parking activity within firms. An expansion factor would be required to analyze the full extent of demand for overnight parking before the fixed supply by MRAs can be considered. Methods to estimate the supply can be completed by methods such as models suggested by Nevland et al. (2020).

The months of February to July of the 2020 year are designated as the pandemic scenario; however, the pandemic has changed significantly by the publication of this document which may have different implications for freight parking trends. A larger analysis of pre-pandemic years before 2019 and post-pandemic years after 2020 may help provide a more extensive view of the pandemic's impact. The land use analysis is also based on designations in 2019; therefore, specific parcels of land may have changed their land use category.

The Region of Peel is a major transportation hub with many freight facilities, including distribution centres and rest areas, but not all facilities can be considered in the analysis. This thesis identified the most widely used facilities observed by the GPS data and denoted them as major distribution centres and major rest areas. Many of the firms identified in the study may be outdated in their existence, location, and/or level of activity. Moreover, the analysis of new locations for Scenario B and Scenario C is conducted under the assumption that land is available to construct these rest areas with no conflicts related to physical infrastructure or political will.

7.3 Concluding Remarks

This study is conducted to determine truck parking activity trends in the Region of Peel during a pandemic scenario and compare it with the pre-pandemic condition. The pandemic scenario is designated as the time period during the first wave of the pandemic when Covid-19 was a novel virus with significant uncertainty. Truck drivers, in particular, are also identified as critical workers during this pandemic and are also noted to be disproportionally affected by the illness (Region of Peel, 2021a). ATRI GPS data is processed to determine the parking activities within the Region.

When considering land use, the data is used to determine if freight parking favours specific land uses. In general, industrial and commercial freight parking is mainly concentrated in the Region's main employment areas that surround Pearson Airport and possess the most freight parking activity in the region. However, increases in the town of Caledon were noted during 2020, particularly for MDCs in Bolton. The analysis determined a large amount of truck parking in areas designated as low-density residential in Caledon compared to the two other cities in the region. In general, the trends for the town are separate from the other two municipalities and analysis specific to the town can be of specific research interest.

Truck drivers face issues with access to distribution centres and need accessible rest areas that provide adequate amenities. The P-median problem provides a tool to determine the best locations where these drivers could rest before conducting their work at MDCs. The problem is used to determine critical areas in which locations should be proposed for new rest areas.

The target audience for the output of this analysis would be provincial health agencies who can identify and consider major MRAs to implement and enforce public health measures to mitigate pandemic spread. However, in the year 2023, the pandemic may not be a major societal issue that is considered by the general populace. However, the analyses can be applied to other limited resource problems. Applications of this work can be considered in the field of disaster management. Infrastructure disruptions such as electricity blackouts and telecommunications outages are areas where critical MRAs should be identified as a limited resource. In other words, the pandemic is not the only context in which the output of this thesis can be considered.

For all of the analyses above, additional study years can be included to determine long-term trends. The various waves of the pandemic can also be defined to track the implications over time. Further analysis can also be considered based on the methods presented in Chapter 4.4. With the expansion of the dataset to be representative of the population, a capacity-constrained P-median model can be considered. A model considering the minimization of exposure based on reducing personal contact can be optimized. Expanding the study area to consider more jurisdictions can be considered with algorithms such as Mu & Tong's (2020) approach using sub-P-median models. Finally, for all of the above analyses, the travel times generated can be varied based on different traffic conditions, especially the reduced flow that is experienced during the pandemic.

REFERENCES

Bagger, N.-C. F., van der Hurk, E., Hoogervorst, R., & Pisinger, D. (2022). Reducing disease spread through optimization: Limiting mixture of the population is more important than limiting group sizes. Computers & Operations Research, 142, 105718. https://doi.org/10.1016/j.cor.2022.105718

Bajunirwe, F., Izudi, J., & Asiimwe, S. (2020). Long-distance truck drivers and the increasing risk of Covid-19 spread in Uganda. *International Journal of Infectious Diseases*, *98*, 191–193. https://doi.org/10.1016/j.ijid.2020.06.085

Banerjee, I., Lee, J. ho, Jang, K., Pande, S., & Ragland, D. (2009). Rest Areas—Reducing Accidents Involving Driver Fatigue. 333. https://dot.ca.gov/-/media/dot-media/programs/research-innovation-system-information/documents/final-reports/ca09-1092-finalreport-a11y.pdf

Baumol, W. J., & Wolfe, P. (1958). A Warehouse-Location Problem. *Operations Research*, *6*(2), 252–263.

Boris, C., & Johnson, M. A. (2015). Managing Critical Truck Parking Tech Memo #1: Commercial Driver Perspectives on Truck Parking. 23. https://truckingresearch.org/wp-content/uploads/2015/09/Managing-Critical-Truck-Parking-Tech-Memo-1-FINAL-09-2015.pdf

Brampton Flight Centre. (2023). Continued Excellence in Canadian Aviation & Pilot Training. Brampton Flight Centre. https://www.bramptonflightcentre.com/

Bunn, T. L., Slavova, S., & Rock, P. J. (2017). Association between commercial vehicle driver at-fault collisions involving sleepiness/fatigue and proximity to rest areas and truck stops. *Accident Analysis & Prevention*, *126*, 3–9. https://doi.org/10.1016/j.aap.2017.11.022

CDC. (2021). How Covid-19 Spreads https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/how-covid-spreads.html

Chatterjee, A., & Wegmann, F. J. (2000). Overnight Truck Parking Along Tennessee's Interstate Highways and Rest Areas. *Transportation Research Record: Journal of the Transportation Research Board*, *1734*(1), 64–68. https://doi.org/10.3141/1734-10

Chen, M., Zhao, T., Lee, J., & Lee, H. (2023). Developing a Decision-Making Process of Location Selection for Truck Public Parking Lots in Korea. *Sustainability*, *15*(2), Article 2. https://doi.org/10.3390/su15021467

City of Brampton | By-laws | Traffic By-law. (2020). https://www.brampton.ca/EN/City-Hall/Bylaws/Pages/Traffic-By-law.aspx

City of Mississauga (2020). Traffic By-Law (Mississauga, Ontario, Canada). https://www.mississauga.ca/publication/traffic-by-law/

Cooper, L. (1963). Location-Allocation Problems. *Operations Research, 11*(3)*,* 331–343. https://doi.org/10.1287/opre.11.3.331

Corro, K. D., Akter, T., & Hernandez, S. (2019). Comparison of Overnight Truck Parking Counts with GPS-Derived Counts for Truck Parking Facility Utilization Analysis. *Transportation Research Record: Journal of the Transportation Research Board, 2673*(8), 377–387. https://doi.org/10.1177/0361198119843851

Crizzle, A. M., Toxopeus, R., & Malkin, J. (2020). Impact of limited rest areas on truck driver collisions in Saskatchewan: A mixed-methods approach. *BMC Public Health, 20*(1), 971. https://doi.org/10.1186/s12889-020-09120-7

Davis, R. E. L. (1997). Commercial Driver Rest and Parking Requirements: Making Space for Safety. *Transportation Research Record: Journal of the Transportation Research Board*, *1595*(1), 46–52. https://doi.org/10.3141/1595-08

DMTI Spatial Inc (2020). DMTI Enhanced Points of Interest. https://www.dmtispatial.com/canmap

Ferguson, M. R., Lavery, T. A., & Higgins, C. D. (2014). Truck Freight Generators & Attractors in the Province of Ontario. 139. https://macsphere.mcmaster.ca/bitstream/11375/18913/1/MITL_Truck_Generators_Feb_28th.pdf

FMCSA. (2022). *Electronic Logging Devices | FMCSA*. https://www.fmcsa.dot.gov/hours-service/elds/electronic-logging-devices

Forrest, J., Ralphs, T., Vigerske, S., Santos, H. G., Hafer, L., Kristjansson, B., jpfasano, Straver, E., Lubin, M., Goossens, J.-W., rlougee, jpgoncal1, Brito, S., h-i-gassmann, tosttost, xmunoz, Saltzman, M., Pitrus, B., to-st, & Matsushima, F. (2023). COIN-OR Branch and Cut. https://github.com/coin-or/Cbc

Garber, N. J., & Wang, H. (2004). Estimation of the demand for commercial truck parking on interstate highways in Virginia: Final report. https://rosap.ntl.bts.gov/view/dot/20450

Gingerich, K., Maoh, H., & Anderson, W. (2016). Classifying the purpose of stopped truck events: An application of entropy to GPS data. Transportation Research Part C: Emerging Technologies, 64, 17–27. https://doi.org/10.1016/j.trc.2016.01.002

Government of Canada, S. C. (2021, February 23). Crossing the border during the pandemic: 2020 in review. https://www150.statcan.gc.ca/n1/pub/45-28-0001/2021001/article/00007-eng.htm

Government of Ontario (2020). Emergency Management and Civil Protection Act. O Reg. 82/20 s.2

Griffith, D. A., & Fischer, M. M. (2013). Constrained variants of the gravity model and spatial dependence: Model specification and estimation issues. *Journal of Geographical Systems*, *15*(3), 291–317. https://doi.org/10.1007/s10109-013-0182-7

GTAA. (2020). GTAA Annual Report 2020 – Healthy Airport. https://www.torontopearson.com/-/media/project/pearson/content/corporate/who-we-are/pdfs/annual-reports/2020-annual-report-narrative_1-43.pdf?modified=20210715220737

Harvey, L. (2022, October 4). Here's when Toronto traffic jams are the worst, according to the data. Thestar.Com. https://www.thestar.com/news/gta/2022/10/04/heres-when-torontos-traffic-jam-are-worst-according-to-the-data.html

Indriasari, V., Mahmud, A. R., Ahmad, N., & Shariff, A. R. M. (2010). Maximal service area problem for optimal siting of emergency facilities. *International Journal of Geographical Information Science*, *24*(2), 213–230. https://doi.org/10.1080/13658810802549162

Jung, S., Joo, S., & Oh, C. (2017). Evaluating the effects of supplemental rest areas on freeway collisions caused by drowsy driving. Accident Analysis & Prevention, 99, 356–363. https://doi.org/10.1016/j.aap.2016.12.021

Kim, H., Goodchild, A., & Boyle, L. N. (2021). Empirical analysis of commercial vehicle dwell times around freight-attracting urban buildings in downtown Seattle. *Transportation Research Part A: Policy and Practice*, *147*, 320–338. https://doi.org/10.1016/j.tra.2021.02.019

Kim, K. (2021). Impacts of Covid-19 on transportation: Summary and synthesis of interdisciplinary research. Transportation Research Interdisciplinary Perspectives, 9, 100305. https://doi.org/10.1016/j.trip.2021.100305

Kinjarapu, A., Demissie, M. G., Kattan, L., & Duckworth, R. (2021). Applications of Passive GPS Data to Characterize the Movement of Freight Trucks—A Case Study in the Calgary Region of Canada. *IEEE Transactions on Intelligent Transportation Systems*, 1–16. https://doi.org/10.1109/TITS.2021.3093061

Land Information Ontario. (2023). Municipal Boundary—Upper Tier and District—Overview. Municipal Boundary - Upper Tier and District. Retrieved, from https://www.arcgis.com/home/item.html?id=11be9127e6ae43c4850793a3a2ee943c

Lemke, M. K., Apostolopoulos, Y., & Sönmez, S. (2020). A novel Covid-19 based truck driver syndemic? Implications for public health, safety, and vital supply chains. *American Journal of Industrial Medicine*, *63*(8), 659–662. https://doi.org/10.1002/ajim.23138

Lightstone, A., & Duggal, M. (2017). REGION OF PEEL – COMMODITY FLOW AND NETWORK ANALYSIS. 8. http://ctrf.ca/?page_id=4419

Mason, A.J. (2020), "OpenSolver – An Open Source Add-in to Solve Linear and Integer Progammes in Excel", *Operations Research Proceedings 2011, eds. Klatte, Diethard, Lüthi, Hans-Jakob, Schmedders, Karl, Springer Berlin Heidelberg pp 401-406, 2012*, http://dx.doi.org/10.1007/978-3-642-29210-1_64, http://opensolver.org

McLean, A. (2016). Battling Blind Spots: Hours of Service Regulations and Contentious Mobilities in the BC-Based Long Haul Trucking Industry. *The Canadian Journal of Sociology / Cahiers Canadiens de Sociologie*, *41*(3), 277–298.

Ministry of Transportation. (2011). *The Greater Golden Horseshoe Model (GGHM)*. Retrieved January 1, 2023, from https://icorridor-mto-on-ca.hub.arcgis.com/pages/gghm

Ministry of Transportation. (2020). Traffic Volume Data. https://www.library.mto.gov.on.ca/SydneyPLUS/TechPubs/Portal/tp/tvSplash.aspx

Mladenović, N., Brimberg, J., Hansen, P., & Moreno-Pérez, J. A. (2007). The p-median problem: A survey of metaheuristic approaches. *European Journal of Operational Research*, *179*(3), 927–939. https://doi.org/10.1016/j.ejor.2005.05.034

Motor Transport Act. *Commercial Vehicle Drivers Hours of Service Regulations.* SOR/2019-165. https://laws-lois.justice.gc.ca/eng/regulations/SOR-2005-313/FullText.html

Mu, W., & Tong, D. (2020). On solving large p-median problems. Environment and Planning B: Urban Analytics and City Science, 47(6), 981-996. https://doi.org/10.1177/2399808319892598

Murad, A., Faruque, F., Naji, A., & Tiwari, A. (2021). Using the location-allocation P-median model for optimising locations for health care centres in the city of Jeddah City, Saudi Arabia. *Geospatial Health*, *16*(2). https://doi.org/10.4081/gh.2021.1002

Nevland, E. A., Gingerich, K., & Park, P. Y. (2020). A data-driven systematic approach for identifying and classifying long-haul truck parking locations. *Transport Policy*, *96*, 48–59. https://doi.org/10.1016/j.tranpol.2020.04.003

OnRoute. (2022). https://www.onroute.ca/locations

Park, P., Gingerich, K., Asgary, A., Annalingam, E. (2021). Mobility Interventions to Protect Supply Chain Workers during Pandemics. Transport Canada.

Phibbs, C. S., & Luft, H. S. (1995). Correlation of Travel Time on Roads versus Straight Line Distance. Medical Care Research and Review, 52(4), 532–542. https://doi.org/10.1177/107755879505200406

Pozoukidou, G., & Chatziyiannaki, Z. (2021). 15-Minute City: Decomposing the New Urban Planning Eutopia. Sustainability, 13(2), Article 2. https://doi.org/10.3390/su13020928

Rad, T. G., & Alimohammadi, A. (2021). Modeling relationships between the network distance and travel time dynamics for assessing equity of accessibility to urban parks. Geo-Spatial Information Science, 24(3), 509–526. https://doi.org/10.1080/10095020.2020.1858189

Region of Peel. (2017). Goods Movement Strategic Plan 2017-2021. 56. https://www.peelregion.ca/officialplan/review/pdf/goods-movement-strategic-plan.pdf

Region of Peel. (2021a). Covid-19 and Truck Drivers in Peel. https://www.peelregion.ca/coronavirus/_media/truck-drivers-final.pdf

Region of Peel. (2021b). Peel Data Centre. https://data.peelregion.ca/

Sadeghi, J. (2018). A method for solving the transportation problem. Journal of Statistics and Management Systems, 21(5), 817–837. https://doi.org/10.1080/09720510.2018.1453682

Sert, E., Hedayatifar, L., Rigg, R. A., Akhavan, A., Buchel, O., Saadi, D. E., Kar, A. A., Morales, A. J., & Bar-Yam, Y. (2020). Freight Time and Cost Optimization in Complex Logistics Networks. *Complexity*, *2020*, e2189275. https://doi.org/10.1155/2020/2189275

Sridharan, R. (1995). The capacitated plant location problem. *European Journal of Operational Research*, *87*(2), 203–213. https://doi.org/10.1016/0377-2217(95)00042-O

Stone, M. (2020). From Toronto to Minneapolis – the effect of Covid-19 on traffic. , https://www.traffictechnologytoday.com/news/data/from-toronto-to-minneapolis-the-effect-of-covid-19-on-traffic.html

Tadić, S., Krstić, M., Stević, Ž., & Veljović, M. (2023). Locating Collection and Delivery Points Using the p-Median Location Problem. Logistics, 7(1), Article 1. https://doi.org/10.3390/logistics7010010

Teranet. (2020). https://www.teranet.ca/ontario-parcel/

Town of Caledon. (2019). By-laws. Traffic By-law (Consolidation) https://www.caledon.ca/modules/document/document.aspx?param=lE51zSXnfjLHs6D5Ktlo7geQuAleQuAl

Walsh, M. (2020). Truck drivers are being denied basic necessities as they deliver essentials in this pandemic. The Globe and Mail. https://www.theglobeandmail.com/politics/article-truck-drivers-are-being-denied-basic-necessities-as-they-deliver/

Yang, K., Wang, R., He, H., Yang, X., & Zhang, G. (2021). Multi-supply multi-capacitated p-median location optimization via a hybrid bi-level intelligent algorithm. Computers & Industrial Engineering, 160, 107584. https://doi.org/10.1016/j.cie.2021.107584

Yang, X., Sun, Z., Ban, X. J., & Holguín-Veras, J. (2014). Urban Freight Delivery Stop Identification with GPS Data. Transportation Research Record, 2411(1), 55–61. https://doi.org/10.3141/2411-07

Yu, J. G., Selby, B., Vlahos, N., Yadav, V., & Lemp, J. (2021). A feature-oriented vehicle trajectory data processing scheme for data mining: A case study for Statewide truck parking behaviors. *Transportation Research Interdisciplinary Perspectives*, *11*, 100401. https://doi.org/10.1016/j.trip.2021.100401

APPENDIX A – FULL LIST OF RANKED DISTRIBUTION CENTRES BY ZONE

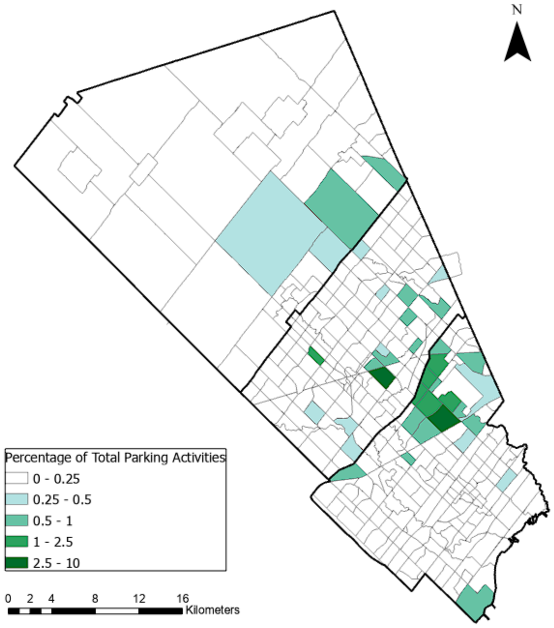
Table A-1 Top 50 DCs within the Region of Peel in 2019

TAZ Rank	City	Number of DCs at TAZ	Percentage at TAZ
1	Mississauga	4	7.62
2	Brampton	1	3.04
3	Mississauga	2	1.97
4	Brampton	2	1.44
5	Mississauga	2	1.08
6	Mississauga	3	1.02
7	Brampton	1	0.85
8	Brampton	2	0.81
9	Brampton	3	0.80
10	Mississauga	1	0.79
Subtotal		**21**	**19.42**
11	Brampton	1	0.72
12	Brampton	2	0.69
13	Mississauga	1	0.66
14	Mississauga	2	0.62
15	Mississauga	1	0.59
16	Mississauga	1	0.58
17	Brampton	2	0.55
18	Mississauga	1	0.52
19	Brampton	1	0.49
20	Mississauga	1	0.37
21	Brampton	1	0.35
22	Brampton	1	0.34
23	Mississauga	1	0.32
24	Caledon	1	0.30
25	Brampton	1	0.30
26	Mississauga	1	0.29
27	Mississauga	1	0.26
28	Mississauga	1	0.25
29	Brampton	1	0.24
30	Brampton	1	0.21
31	Brampton	1	0.20
32	Mississauga	1	0.18
33	Brampton	1	0.18
34	Caledon	1	0.18
35	Mississauga	1	0.17
36	Brampton	1	0.16
Subtotal		**50**	**29.10**

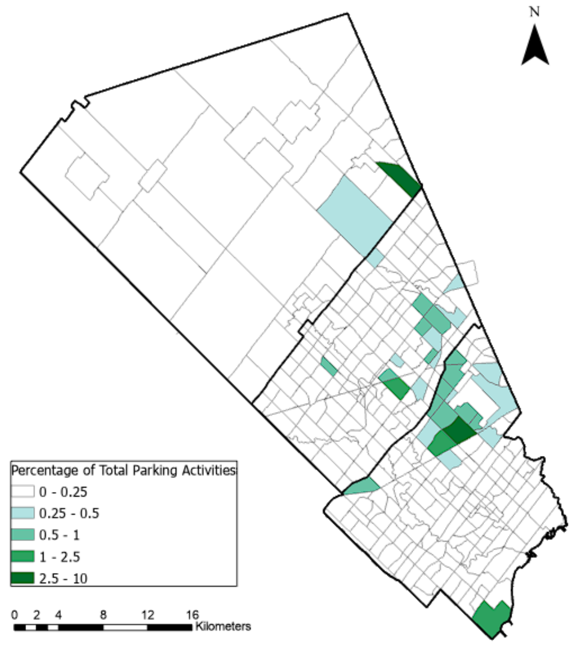
Table A-2 Top 50 DCs within the Region of Peel in 2020

TAZ Rank	City	Number of DCs at TAZ	Percentage at TAZ
1	Mississauga	5	4.27
2	Mississauga	1	3.74
3	Brampton	2	2.14
4	Brampton	1	1.68
5	Mississauga	2	1.62
6	Mississauga	3	1.34
7	Caledon	3	1.16
8	Brampton	3	1.15
9	Brampton	1	1.08
10	Mississauga	1	0.97
Subtotal		**22**	**19.16**
11	Mississauga	1	0.85
12	Mississauga	2	0.83
13	Caledon	1	0.74
14	Brampton	1	0.74
15	Brampton	1	0.73
16	Mississauga	1	0.65
17	Mississauga	1	0.63
18	Mississauga	1	0.61
19	Mississauga	1	0.55
20	Mississauga	2	0.55
21	Brampton	1	0.54
22	Mississauga	1	0.51
23	Mississauga	1	0.46
24	Brampton	1	0.46
25	Brampton	1	0.43
26	Mississauga	1	0.38
27	Brampton	1	0.37
28	Brampton	1	0.36
29	Caledon	1	0.36
30	Brampton	1	0.36
31	Mississauga	1	0.28
32	Mississauga	1	0.26
33	Brampton	1	0.26
34	Brampton	1	0.24
35	Brampton	1	0.24
36	Mississauga	1	0.23
Subtotal		**50**	**31.78**

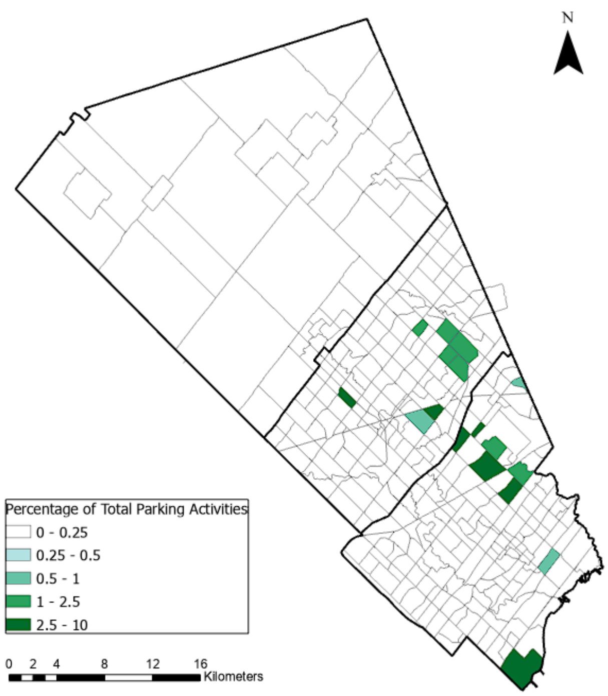
APPENDIX B – OVERNIGHT PARKING ACTIVITIES BY CATEGORY



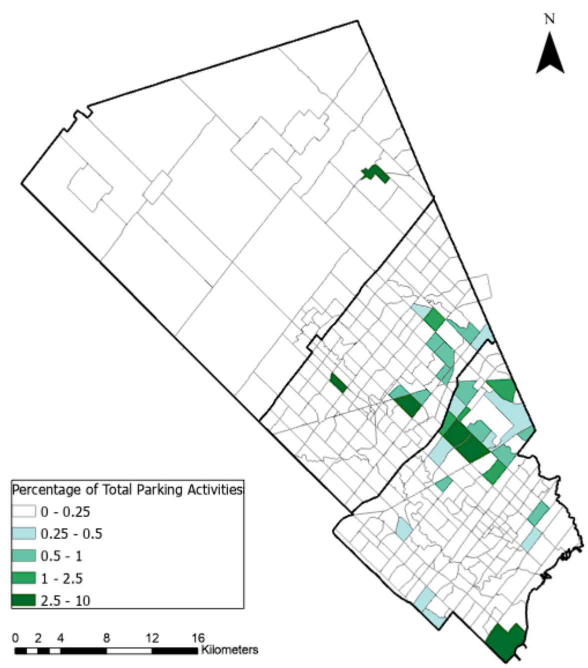
a) Minor DCs and Rest Areas - 2019



b) Minor DCs and Rest Areas - 2020



c) Other Firms - 2019



d) Other Firms - 2020

Figure B-1 Top Firms based on Overnight Parking

APPENDIX C – ADDITIONAL TRAVEL TIME FACTORS

The time factors are presented below with additional analysis. For the 2020 year, one of the rest area facilities only served a singular MDC. This facility is the one location by Airport Road north of Pearson Airport. The MDC is also only served by that location. An additional coefficient is determined that excluded the MDCs and the one MRA. Additional coefficients were also obtained for both travel only within weekdays and travel only within weekdays. All coefficients within 2019 are still not statistically significant, and the weekend coefficient for 2020 is also not statistically significant.

Table C-1 Additional θ Travel Time Factors

Year	Coefficient θ	t-stat	p-value	Coefficient α	t-stat	p-value	R^2
2019	0.0211	1.78	0.08	0.4573	3.79	0.00	0.08
2020	0.0314	4.68	0.00	0.4448	4.68	0.00	0.10
Weekday 2019	0.0170	1.45	0.15	0.4160	3.68	0.00	0.08
Weekday 2020	0.0306	3.66	0.00	0.3983	4.46	0.00	0.09
Weekend 2019	0.0063	1.42	0.16	0.1475	4.13	0.00	0.09
Weekend 2020	0.0015	0.31	0.77	0.2041	5.07	0.00	0.09

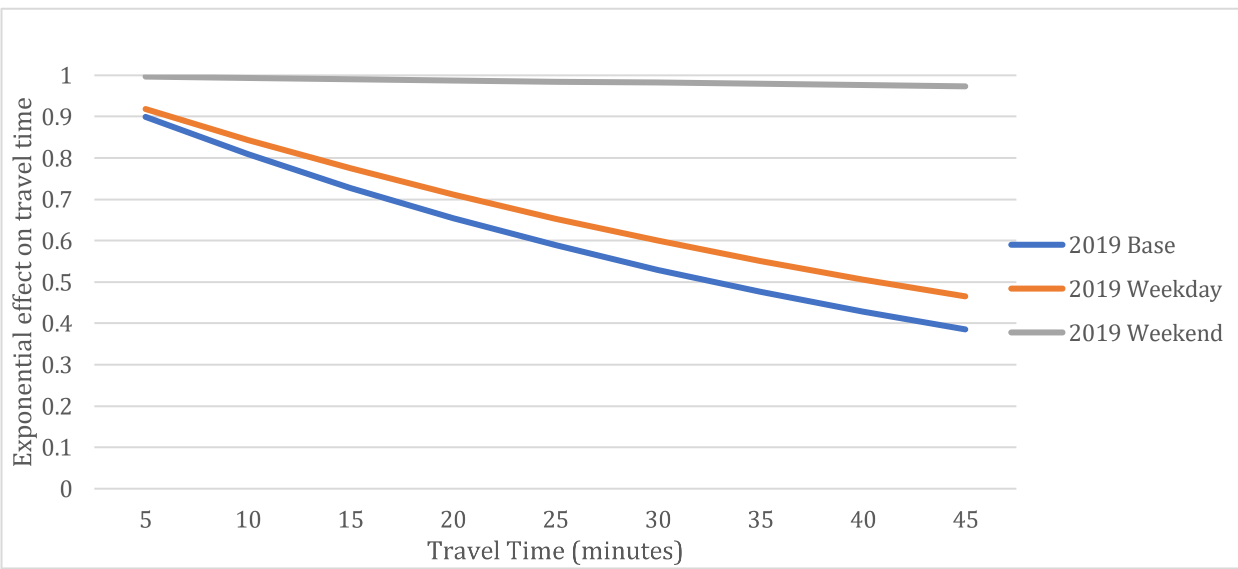


Figure C-1 Time Factor Plots for θ - 2019

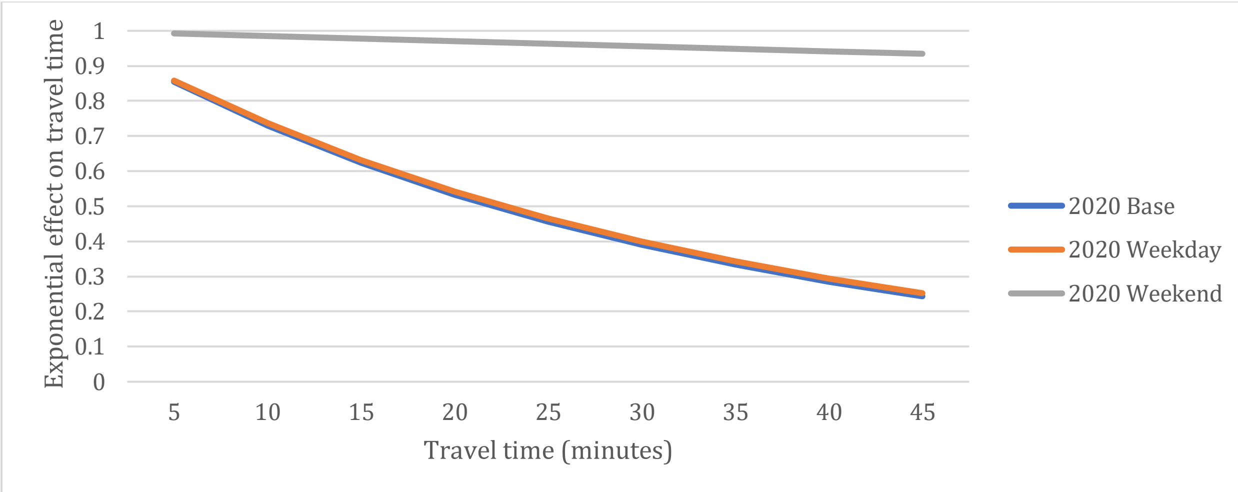


Figure C-2 Time Factor Plots for θ – 2020