TRUCK PARKING IN URBAN AREAS: APPLICATION OF CHOICE MODELLING WITHIN TRAFFIC MICROSIMULATION

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Abstract

Urban truck parking policies include time restrictions, pricing policies, space management and enforcement. This paper develops a method for investigating the potential impact of truck parking policy in Canadian urban areas. An econometric parking choice model is developed that accounts for parking type and location. A traffic simulation module is developed that incorporates the parking choice model to select suitable parking facilities/locations. The models are demonstrated to evaluate the impact of dedicating on-street parking in a busy street system in the Toronto CBD. The results of the study show lower mean searching time for freight vehicles when some streets are reserved for freight parking, accompanied by higher search and walking times for passenger vehicles.

Introduction

Central business districts (CBDs) are major destinations for goods pickup and delivery in Canada's urban centres. "Last mile" delays in CBDs are one of the most expensive components of urban freight (O'Laughin, 2007). In this "last mile", truckers must navigate congested urban streets and search for appropriate parking. When parking is unavailable or inappropriately located, delivery vehicles frequently park illegally, often considering the parking tickets as a cost of doing business. This cost is increasing over time. From 2006, to 2009 parking fines in Toronto increased 70%, and there is little evidence that illegal parking problems is being reduced. In Toronto, FedEx, UPS and Purolator paid an estimated $2.5M in parking fines in 2009 (Haider, 2009).

The problem is significant and growing. The Toronto CBD, for example, receives a daily average of 81,000 packages from express delivery alone (Haider, 2009). Parking and loading spaces are limited in the CBD because many of buildings were constructed before the invention of the automobile. Increasing land values have resulted in the conversion of surface parking lots to high-rise buildings, which in turn are increasing the demands for goods delivery.

While parking issues are also common in other large North American cities, many of these other cities are searching for innovative ways to more effectively manage truck parking. Effective truck parking policy has potential to reduce logistics costs, improve congestion, improve safety and ultimately make Canadian cities more competitive to attract business.

Urban policy makers are in need of data and decision support tools to identify impacts of parking policy scenarios such as dedicated on-street parking for commercial vehicles, time restrictions, and pricing policy. Traffic simulation tools are increasingly popular for urban traffic analysis, however, they do not currently provide sufficient representation of parking. Parking simulation models have been developed, but these models are for passenger parking, which is behaviourally different than truck parking. Econometric models of parking choices have also been developed, but again are limited to passenger cars (Habib et al., 2012).

This paper explores the potential of truck parking policies and develops a novel tool for assessing the impacts of parking policy. First, a review of strategies for dealing with truck parking is provided. Second, a truck parking type and location choice model is developed using data from a truck parking survey conducted in the summer of 2010. Third, a traffic simulation model is developed for a small study area in the Toronto CBD. The model specifically represents on-street parking, off-street surface parking lots, parking garages, truck loading docks, and alleyways suitable for truck loading/unloading. A module for truck parking behaviour is incorporated in this simulation environment that is capable of assessing the traffic impact of changes in parking policy on truck parking choice. Finally, the model is applied to test the impact of two simple truck parking scenarios on measures of effectiveness such as time to find parking, and walking distance to the final destination.

Literature Review

In dense CBDs, curb space is a scarce resource with high demands from a variety of users. Curb space management policies impact road congestion, business vitality, urban aesthetics, and pedestrian safety and comfort (Zalewski et al., 2011). On-street parking is often the focus of parking management practices where there is not ample supply to fulfill the demand. Policy makers have generally responded to this problem by promoting parking turnover using control time limits and parking pricing. Higher meter rates, on the other hand, are endorsed by those who believe time limitations are challenging to monitor and enforce. Shoup argues that parking meters can create curb vacancies by directing a portion of drivers to off-street parking facilities (Shoup, 2006). This would reduce cruising for curb parking which can reduce congestion.

In addition to the indirect effect of passenger vehicle parking policies on freight vehicles, loading zone regulations and freight restrictions directly impact freight deliveries. In response to recent freight vehicle operations issues, the Federal Highway Administration (FHWA) developed case studies in some of the major cities of the United States (Los Angeles, New York City, Washington DC, and Orlando) to document prominent goods movement strategies (FHWA, 2009). Freight parking strategies employed in these cities included time restrictions, pricing strategies, parking space management, and parking enforcement.

Time Restrictions

A common freight parking strategy used in many cities is time of day loading zone restrictions. The goal of such time restrictions is to separate commercial vehicles and passenger vehicles in urban areas temporally instead of spatially. In Manhattan, the New York City Department of Transportation (NYCDOT) is planning to implement delivery windows to designate curbside parking for freight vehicles in the morning and create better parking opportunities for passenger vehicles later in the day. They have learned that 65% of all deliveries occur before 12 PM and granting exclusive parking access to freight vehicles during these hours can reduce traffic congestion. A similar strategy is used in Philadelphia where loading zone restrictions (subject to parking enforcement) encourage local businesses to receive any deliveries before 10:00 a.m. (Zalewski et al., 2011). Jaller et. al. (2011) estimated that, in Manhattan, shifting approximately 20% of freight traffic to off-peak hours would minimize the number of over capacity parking locations. Any more than this, and the off-peak hours begin to suffer the same capacity problems as occur during peak hours.

Pricing Strategies

Pricing strategies, in general, encourage greater turnover of both passenger and freight vehicles to create better parking opportunities for newly arriving vehicles. The District Department of Transportation (DDOT) in Washington, DC has installed loading zone meters along K Street in response to all-day parking of commercial vehicles. The meters charge commercial vehicles $1 per hour and allow a limit of two hours for parking. The NYCDOT has also implemented a pricing strategy using the Muni-meter program that uses an escalating rate structure of $2 for one hour, $5 for two hours, and $9 for three hours. This strategy has led to considerable reductions of dwell times (160 minutes to 45 minutes) and highlights the need for research in studying the impact of different hourly pricing combinations.

Space Management

Commercial vehicles can improve efficiency if ample curbside space is reserved for them. The NYCDOT encourages smaller jurisdictions to designate part of the curbside or even individual spaces to commercial vehicles. The DDOT and Downtown DC Business Improvement District (BID) in Washington, DC have also extended loading zones from 40 feet to 100 feet in length in K Street and moved commercial loading zones to the approach end of each block wherever possible.

Parking Enforcement

Parking enforcement responds to lack of regard for parking regulations. For example, the Los Angeles Department of Transportation (LADOT) has initiated an enhanced parking enforcement program called “Tiger Teams”. The program deploys fifteen uniformed traffic control officials and ten tow trucks to enforce parking violations during peak hours. The program improved traffic flow and enhanced goods movement. Washington DC has also adopted a similar program of parking enforcement on K Street in addition to its other curb-space management policies. The NYCDOT reports that enforcement is a critical component for a successful curbside management program. They implemented a pilot program incorporating enforcement in 2002 called THRU Streets (NYCDOT, 2004). This program consisted of the designation of THRU streets, where traffic flow was prioritized, and non-THRU streets, where accessibility was prioritized. On THRU streets, parking was made available on one side only. Enforcement was increased on THRU streets, with the goal of reducing illegal parking and increasing curb clear time. On non-THRU streets, multi-space MUNI meters were installed on both sides of the street, creating approximately 150 additional freight parking spaces in the study area. This pilot program resulted in a decrease in travel times, an increase in network capacity, and increased the percentage of streets free of illegally parked vehicles.

Parking Innovations

Several North American cities have recently incorporated innovative technologies to better manage the available scarce curb space. For example, San Francisco Municipal Transportation Agency (SFMTA) has initiated a comprehensive parking program called SFPark. SFPark collects real-time information using parking sensors and distributes information via the internet and smart phone applications to inform drivers about locations of vacant parking spots. To achieve higher parking availability, SFPark periodically adjusts meter and garage prices to better match the demand. The rates vary by time and location and are adjusted by no more than 50c per hour down or 25c per hour up. The objective of the system is to adjust rates so that at least one vacant on-street parking spot is available on each block.

Data and Method

The new data collected for this research included a survey of truck drivers, a count of truck parking events and a complete inventory of parking supply in the Toronto CBD (area between Queen St., Simcoe St., Front St. and Victoria St). In August of 2010, driver interviews and truck parking counts were conducted to determine the demand for parking and loading. The interviews of truck drivers were conducted by a surveyor who targeted parked commercial vehicles on individual road segments on weekdays between the hours of 9:00 AM to 3:00 PM. The interviews collected arrival time, departure time, parking location, type of vehicle, the company that owned the commercial vehicle, the commodity delivered and the final destination of the delivery. The survey instrument is shown in Appendix A. While conducting surveys, the interviewer also counted the total number of trucks parking in the road segment. Overall, 200 driver interviews and observation of 1940 parking events were conducted. On average, approximately 10% of trucks parking in each segment were subject to a driver interview. A broad variety of commercial vehicle types and commodity types were covered in the survey, resulting in a reasonable representation of truck movements across the Toronto CBD. Details of the data collection effort are presented in (Kwok, 2010).

Figure 1 shows the area in the Toronto CBD that was selected as the study area. The locations marked with white squares on this figure represent some of the 60 most heavily ticketed locations in Toronto as reported by the Canadian Courier Logistics Association (CCLA). The locations marked with black squares are among the 10 most ticketed locations. This area also contains a mix of major two-way arterial streets (Bay, Queen, and Yonge), major one-way streets (Richmond and Adelaide), and small backstreets (York, Temperance, and Sheppard). There is also a good mix of on-street parking, loading bays, surface lots, and parking garages in this area. The area consists mostly of high rise buildings including the Bay Adelaide Centre (51 storey office complex), the Sheraton Centre (43 storey hotel), the Richmond Adelaide Centre (12 storey office complex) and several other 12 – 20 storey office towers. Retail and dining establishments are present at street level and office space is generally located above street level.

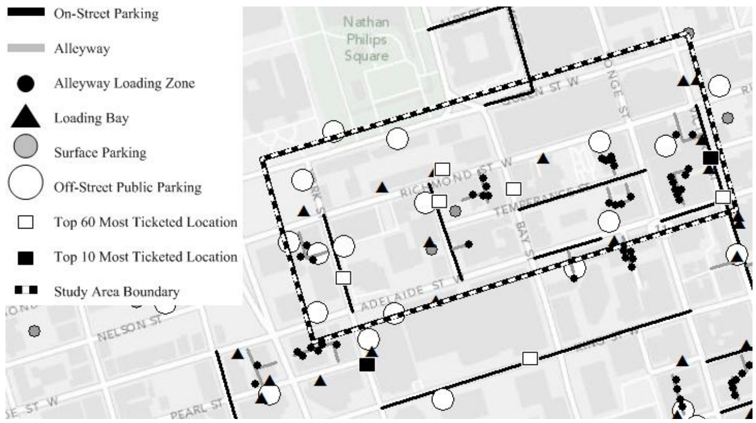

Fig. 1- Study area in the Toronto CBD

The modelling methods developed in this paper include a parking choice model and a parking simulation model. These models are described in the following sections.

Parking choice model

The parking choice model is an econometric discrete choice model of parking type (on-street, off-street, illegal) and location choice. A binary logit model is developed to determine the probability of parking at a parking location for every simulated vehicle in the study area network. This model can be written as (Ben-Akiva and Lerman, 1985):

where is a vector of estimated parameters and is a vector of characteristics of the current parking location *i*. The binary logit model is based on data from the driver interviews, in which the selected parking location was identified. The data were processed to identify the last two parking locations that driver would have passed and rejected en route to his chosen parking location, as follows. First, the address of the parking event and the address of the previous stop were found. Next, Google Maps was used to find the driving route from the previous stop to the parking event. From the parking inventory, the previous two appropriate parking facilities (i.e able to accommodate the vehicle type) that the driver would have passed en route to the parking location were identified (if such facilities existed). Finally, the walking distance to the delivery destination and other relevant attributes of the parking spot were determined.

The binary logit model for freight vehicle parking location choice is sensitive to parking availability, distance from the final shipment destination, and parking facility type. The parameters of this model were estimated using a maximum likelihood process. The estimated values for these coefficients are statistically significant if the absolute value of the '*t*' statistic is greater than 1.96 for the 95% confidence interval. The estimated parameters are summarized in Table 1.

Table 1- Binary choice model for freight vehicle parking location

Log Likelihood	-84.35
Pseudo *R*-squared	0.3086

Variable	Coefficient	*t*-Stat
Distance	-6.23E-03	-3.87
On Street	-1.61	-4.11
Loading Bay	2.21	2.09
Constant	2.12	6.09

Parking Simulation Model

A P.M. peak hour parking simulation model is developed for the study area in the Paramics traffic simulation software. The P.M. peak hour was selected based on field observations showing that this is when the greatest degree of parking activity was occurring. The Toronto CBD experiences greater levels of activity in the P.M. peak house because: A large number of workers are commuting out of the CBD at this time; a large number of people are entering the city to shop eat or go to entertainment; and trucks are near the peak of their deliveries (trucks often avoid the A.M. peak hour because of congestion). The major inputs to this model are a detailed road network, parking facility locations and capacities, and truck and passenger vehicle demand matrices.

The Paramics road network for the study area was extracted from a larger network developed and calibrated for a previous project. Parking facility locations were identified in a comprehensive inventory taken in the summer of 2010 (Kwok, 2010), and were coded into the simulation network.

The data for the development of truck and passenger vehicle demand matrices were retrieved from Toronto's household travel survey (the Transportation Tomorrow Survey - TTS), City of Toronto intersection traffic counts, and the truck parking survey by Kwok (2010). TTS data were used to calculate the passenger vehicle trip generation and attraction for the study area. Truck trip generation and attraction was determined from the truck parking survey. The entry and exit points of inbound and outbound trucks and passenger vehicles were distributed among the roads entering the study area using intersection count data obtained from City of Toronto. Trips though the study area were calculated from the residual intersection counts after inbound and outbound trips had been subtracted. The model assumes no trips had both an origin and destination within the study area.

The parking choice model is integrated within the simulation model. The choice model is called each time a vehicle arrives at a potential parking facility which is within 250m of its final destination. The model then calculates the probability of selecting the targeted parking facility. Using a Monte Carlo simulation and the calculated binary choice probability, the vehicle decides whether to take the parking facility or to keep driving to find a better parking opportunity. Once parked, vehicles dwell at the facility until they reach their parking duration time when they leave the facility and drive to their next destination outside the study area boundaries. Figure 2 is a schematic of the simulation process applied simultaneously to each vehicle. The flowchart is interpreted in the following steps:

1- The simulation model initiates at time T_0.
2- Vehicles are traced if within 250m of their final destination.
3- Traced vehicles evaluate each parking facility they approach using the binary logit model, until one is chosen.
4- When a parking facility is chosen, its capacity is reduced by 1 spot which is taken by the vehicle. Similarly, the capacity of the facility is increased by 1 when the vehicles reaches its dwell time and leaves the facility.
5- The model stops tracing vehicles at the time they reach their dwell time and are dispatched from the parking facility to leave the network.
6- The model terminates when time reaches the simulation duration which is set to 1.5 hours in this study with 0.5 hours of warm-up.

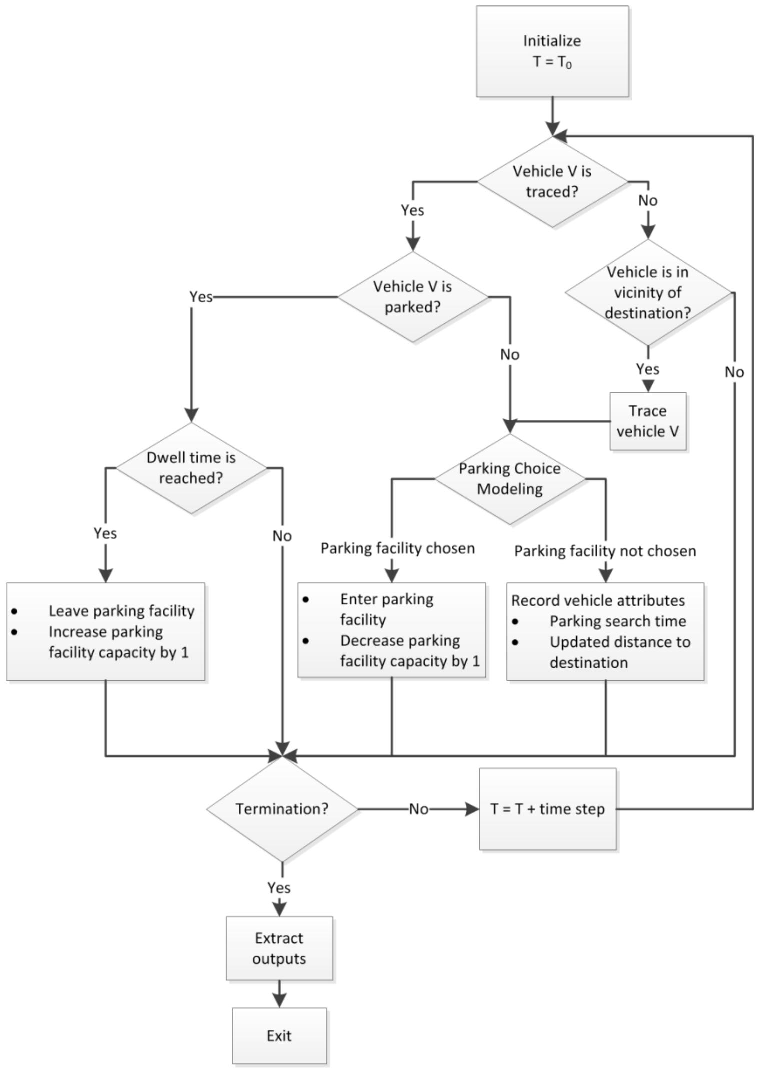

Fig. 2 – Parking simulation model flowchart

Two measures of effectiveness calculated in the model are average search time and average walking distance. Vehicle search time is defined as the difference between the time a vehicle crosses a radius of 250 m of its destination to the time the vehicle finds a spot. Walking distance is defined as the distance between the final destination of the delivery and the parking location. Intuitively, lower values of both measures of effectiveness are more attractive to both parking authorities and users.

Scenarios and Results

The integrated parking choice-simulation model is designed to evaluate various parking policies. To test the model, we apply the THRU Street parking concept. The two assessed parking policy scenarios are the following:

Scenario 1:
Sheppard and Temperance Streets are designated as access streets where access to parking facilities is given only to freight vehicles. Richmond and Adelaide Street are designated as THRU streets where freight parking is prohibited.

Scenario 2:
Sheppard and Temperance Streets are exclusively reserved for freight parking. Freight vehicles are permitted, however, to park elsewhere in the study area.

The results of the scenarios 1 and 2 are compared to the base scenario with no changes to existing parking policy. To account for random variation in the model, 10 runs are executed for each scenario, and mean and standard deviation of each measure of effectiveness is provided. Table 2 presents the measures of effectiveness for the base scenario and two THRU Street scenarios, for each vehicle type.

Table 2- Comparison between base and the THRU Street scenarios

	Search Time (minutes)				Walking Distance (metres)			
	Freight Vehicles		Passenger Vehicles		Freight Vehicles		Passenger Vehicles	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Base Scenario	1.87	1.29	1.50	1.34	67.9	67.2	85.4	69.1
Scenario 1	1.26	1.18	1.61	1.39	81.4	56.3	87.2	68.7
Scenario 2	1.01*	1.1	1.76	1.45	34.8*	45.1	91.2	64.2

Note: changes in means are significantly different from the base scenario with 90% degree of confidence if an asterisk follows the value

Comparison of the three scenarios shows expected differences between the search time and walking distances of both passenger and freight vehicles. Results show lower freight search time values in Scenario 1 compared to the base scenario, (although the difference is not highly statistically significant). This is due to the presence of more vacant spots in the access streets that are now available to freight vehicles. The freight vehicle search time standard deviation is also lower for Scenario 1 because freight vehicles are aware of where vacant spots are and they drive directly to the access streets, thus reducing variability in search time. In Scenario 2, however, mean freight vehicle search time is cut down even more to 1.01 minutes, a significant reduction. This happens because those freight vehicles with destinations other than the access streets that were forced to drive to the access streets in Scenario 1 can now drive directly to their final destination. In general, the standard deviation for search times is relatively high, indicating that some vehicles are able to find parking very quickly while some vehicles spend far more time searching for parking. This is consistent with the reality that if a vehicle does not find parking at a close distance the first time they pass their destination, they may spend significant time travelling around the block to make a second attempt.

Walking distances, on the other hand, show higher mean values in Scenario 1 for freight vehicles. This is due to the nature of the policy. Requiring freight vehicles to park on specific access streets restricts the drivers from parking at a location closer to their destination. Hence, drivers have to walk further to reach their final delivery/pickup locations. The mean freight walking distance value in Scenario 2, however, is significantly lower. This happens because those vehicles that were restricted in Scenario 1 can now drive to their destinations and park at a closer location.

Passenger vehicles, on the other hand, experience different outcomes. Higher mean passenger vehicle searching time results in both scenarios 2 and 3 (although the differences are not highly significant). This is due to a diversion of parking demand from the access streets to other locations where parking is harder to find. On the whole, the results of the three scenarios present an expected tradeoff between measures of effectiveness of passenger and freight vehicles.

Conclusions and Future Directions

The integrated parking behaviour-simulation model presented in this paper is a new approach to parking policy evaluation. The model is able to capture important dimensions of parking activity such as walking distance and search times that are commonly neglected in the literature, and usually not quantified at all in practical decision-making. With some effort the method can be applied in any jurisdiction for which a traffic simulation network, and appropriate information about parking supply and demand are available. While the most crucial applications are in dense urban areas where the greatest competition exists for curb space, smaller urban areas with localized parking hotspots are also potential application areas.

Our results show relationships between parking supply, parking demand, and network attributes (i.e. link travel times). In cases where demand exceeds the available supply, the vehicles cruise around the network to find a spot. Higher link travel times, higher parking demand, and lower parking supply all contribute to increasing parking search times.

To verify that the model provides useful and reasonable results, we apply the model to two scenarios for a small but busy study area in the Toronto CBD. These scenarios dedicate parking on some interior streets to trucks. Our results show reductions in freight vehicle searching time in these scenarios, whereas freight vehicle walking distances depend on the parking policy for other streets in the network. Passenger vehicle search time and walk distances increase. All of these changes are intuitive, lending credibility to the model, and they quantitatively illustrate the tradeoffs that arise in selecting among competing uses of curb space.

The model could be improved and further validated. First, parking spot availability/occupancy driver search time and walking distance were not collected in enough detail for the study area in the parking choice survey. Testing model outcomes against observed values for these critical measures would improve confidence in the model. Second, all trucks are assumed to make parking decisions that conform to a single simple choice function. Couriers, food deliveries and shredding trucks, as examples, all have very different constraints on their parking behaviour that could be represented with more detail if data were available.

This research could be further extended to evaluate the effectiveness of other parking policies such as time restrictions, parking information systems, pricing strategies, and new parking facilities, or requirements for new developments. However, some additional data collection efforts may be required for evaluation of these policies. Additional data can be integrated into the simulation by enhancing the parking choice models to include price variables or prior knowledge of parking availability. Additional measures of effectiveness could also be investigated. In particular, the simulation technique could be extended to quantify the implications of parking policy on congestion, the effects on illegal parking and occupancy rates.

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APPENDIX A: Parking Survey Questionnaire

1.1 – Type of freight carrier
1.2 - TL, LTL or Package
1.3 - Type of freight carried
1.4 – Type of truck driven

2.1 – How long have you been driving for this company?

2.2 – How long have you been driving in downtown Toronto?

2.3 – How familiar are you with parking available in downtown Toronto?

3.1 – What type of fuel does your vehicle use?

4.1 – Currently, where are you parked relative to your destination?

4.2 – List the location(s) of the pickup/delivery or other activity accessed from this parking spot

4.3 – What is the approximate total weight of deliveries from this parking spot?

4.4 – What is the approximate total weight of pickup from this parking spot?

4.5 – What is the approximate total number of boxes/packages/ items delivered and picked-up?

4.6 – Was any special handling equipment used? If so, please describe

4.7 – Did you have difficulty finding a legal parking spot? If so, how long did you spend searching for a spot to parking?

4.8 – Did you have to wait to use a loading zone at this stop? If so, how long did you wait?

4.9 – Do you idle or turn your engine off when making deliveries/pickups? If you do idle, for how long do you do so?

4.10 - Do you understand what the no stopping, standing, parking sign mean?

5.1 – What was the location of your previous stop?

5.2 – What will be the location of your next stop?

5.3 – How many pickups/deliveries/other purpose stops do you expect to have made by the end of today? How many of these are in downtown TO?

5.4 – What are your driving hours for today?

5.5 – What is the location of your depot?

6.1 – What times of the day are the easiest to park legally? The hardest?

6.2 – What makes it hard to park legally at the hardest time of the day? (Select three)

6.3 – Where are the majority of your parked locations at?

6.4 – How many parking tickets do you typically receive daily?

6.5 – Do you agree parking authorities are biased towards commercial vehicles in issuing tickets?

6.6 - Does your company have a parking policy? If so, what is it?

6.7 – What are major barriers for using loading and parking zones?

6.8 – Which area in the downtown is the most frustrating for you to park/load and why?