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# 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 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.



## 1. 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 et al., 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 are being reduced. In Toronto, FedEx, UPS and Purolator paid an estimated \$2.5 M 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 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.

Freight parking issues are common in other North American cities as well. The U.S. Department of Transportation (USDOT) together with the Federal Highway Administration (FHWA) and the Office of Freight Management and Operations prepared a series of case studies documenting best practices for urban goods movement. Reports were prepared for

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Washington DC, Orlando, New York City, and Los Angeles. The purpose of these studies is to investigate initiatives aimed at mitigating congestion and improving efficiency of commercial vehicle operations, including parking (FHWA, 2009).

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. In Section 2, we provide a review of strategies for dealing with truck parking. In Section 3, we develop a truck parking selection model using data from a truck parking survey conducted in the summer of 2010. In Section 4, we develop a traffic simulation model 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 binary logit model for parking selection is incorporated in this simulation environment that is capable of assessing the traffic impact of changes in parking policy on truck parking choice. The model is applied to test the impact of two simple truck parking scenarios on measures of effectiveness such as time to find parking, walking distance to the final destination, and total network travel time. In Section 5, we present the conclusions of this research and suggest future research directions.

## 2. Literature review

The literature can be usefully divided into three parts: freight parking policies, parking simulation models, and parking choice models. In Section 2.1, we describe policies targeting freight vehicle operations and in Sections 2.2 and 2.3 we review the literature on simulation methods and choice models of parking policy analysis, respectively. Section 2.4 summarizes the findings of the literature review and identifies the research gap this work is intended to address.

### *2.1. Freight vehicle parking policies*

In dense CBDs, curb space is a scarce resource with high demands from a variety of users. In these locations, commercial vehicles are competing directly with passenger vehicles for spaces to park. 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. Nevertheless, the generated revenue from parking meters can be spent on public improvement in the metered neighbourhoods. Pasadena is an example where charging market prices (off-street prices) for curb parking has reduced congestion and made the area safer and cleaner from the generated parking revenue (Kolozsvari and Shoup, 2003). Clearly, implementation of any passenger vehicle parking policy indirectly affects the operations of freight vehicle deliveries even if they are not the targeted group. Any policy that produces more vacant spaces on the curbside creates better opportunities for on-street freight parking.

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 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.

#### *2.1.1. 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 AM (Zalewski et al., 2011). Jaller et al. (2013) estimated that, in Manhattan, shifting approximately 20% of freight traffic to off-peak hours would minimize the number of over capacity parking locations.

#### *2.1.2. Pricing strategies*

Pricing strategies, in general, can 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 2 h for parking. The NYCDOT has also implemented a pricing strategy using the Muni-meter program that uses an escalating rate structure of $2 for 1 h, $5 for 2 h, and $9 for 3 h (NYCDOT, 2004). This strategy has led to considerable reductions of dwell times (160–45 min) and highlights the impact of different hourly pricing combinations (Zalewski et al., 2011). The SF*park* program in San Francisco dynamically adjusts the prices of on-street spaces and off-street facilities, with the goal of creating available on-street parking on each block. Over the first year in operation, SF*park* has seen occupancy on overcrowded blocks fall after four of the six price increases (Pierce and Shoup, 2013).

#### *2.1.3. Space management*

Commercial vehicle operations efficiency can improve 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 in Washington, DC have also extended loading zones from 40 feet to 100 feet in length on K Street and moved commercial loading zones to the approach end of each block wherever possible.

#### *2.1.4. 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. 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 an increase in the percentage of streets free of illegally parked vehicles.

### *2.2. Parking simulation*

Parking equilibrium models, which are common in the literature (Arnott and Inci, 2006; Lam et al., 2006; Shoup, 2006; Li et al., 2007; Gallo et al., 2011), are formulated to capture the relationship between various parking activity components such as price of parking and distance to final destination. One of the major drawbacks in such models is lack of regard for the dynamic nature of parking behaviour. These models neglect walking time (distance) and parking availability at different hours of the day. Walking distance (from parking spot to destination) is critical for those highly sensitive to time (such as truck drivers making deliveries). Similarly, representation of the supply of off-street parking can be crucial. Furthermore, the equilibrium models have crude presentation of cruising time which is highlighted as one of the most important features of parking behaviour by Ommeren et al. (2012).

In an attempt to fill in this gap in parking research, Benenson et al. (2008) propose an explicitly space sensitive dynamic model called PARKAGENT to simulate behaviour of individual drivers. This model is structured for two groups of agents (residential and visitor) in the city of Tel Aviv where future surface parking construction is expected. In this research drivers enter the simulation when within 250 m vicinity of their destination and lower their speeds to 25 km/h where they become aware of the need to park. This model is structured to evaluate the impact of additional parking facilities in the residential area but does not capture the impact of the type of parking facility.

Dieussaert et al. (2009) introduce SUSTAPARK which is a spatio-temporal tool simulating both traffic and parking behaviour in a cellular automata structured network. Their parking behaviour model uses a multinomial logit model which is a simplified version of that proposed by Hess et al. (2006). In this MNL structure, agents select their initial parking type from two possible choices (on-street and off-street parking) based on parking features such as search time, egress time, and expected fee which are input to a utility function. However, this initial choice is modified every 30 s according to the re-evaluated parameter values and new utility function. The utility function value for every agent would decrease as cruising time builds up to the point where parking off-street is a more suitable option.

Munuzuri et al. (2002) develop a dynamic parking model for freight vehicles in a microscopic traffic simulator called TRAMOS. In this model private and freight vehicles are assigned different available types of parking facilities, parking choice behaviour, and number of stops for each vehicle type. Private vehicles are assigned one stop whereas freight vehicles are assigned an itinerary of stops, each of which has a specified location and duration. The freight parking choice model is based on a weighting system for each parking facility type as a function of distance to delivery point. For example, at up to 15 m from the delivery point, the choice of loading zone parking has a higher decision weight than on street parking and is more likely to be chosen. The parking choice model for private vehicles, however, is simpler and only a function of the distance covered from the vehicle's origin. Private vehicles are assumed to take the first parking facility when the distance they have travelled has reached a maximum threshold which is 1.25 times the width of the network. This proposed model is only tested on a simple network of four nodes and three links and sufficient analysis is not provided to assess policy.

Waraich and Axhausen (2012) extend MATSim to capture the influence of parking on daily (activity) plan features including travel time, travel mode, and destination choice. Their model reflects, for example, that insufficient or expensive parking may encourage drivers to change their mode of transport or time of departure. MATSim agents iteratively select, among possible daily plans with different utility scores, the one with the best final score (the "fittest alternative"). One of the disadvantages of the proposed model by Waraich and Axhausen (2012) is that it is not completely dynamic, meaning that perfect knowledge of parking availability is available before the trip is made. Clearly, this overlooks the possibility of cruising for parking in cases where drivers arrive to their destination and then start looking for a spot.

### 2.3. Parking choice modelling

Since Van der Goot (1982), only Munuzuri et al. (2002) have considered commercial vehicle parking choice. Axhausen and Polak (1991) estimated two parking choice logit models, one in Germany and the other in the UK. The data used in their research was collected using a stated preference (SP) survey, which the researchers argued was superior to previous studies using revealed preference (RP) data. They found that access time, parking search time, walking time between the parking location and final destination, parking type, and parking fee were all significant factors in selection of a parking location. Another important result from this work was that time spent searching for parking and time spent driving to the general location had significantly different parameters in Germany and the UK.

Teknomo and Hokao (1997) applied a multinomial logit model in Indonesia using an RP data set. Similar to other studies (Van der Goot, 1982; Axhausen and Polak, 1991), they found that walking time, trip duration, parking fee, and parking search time were all significant factors in selecting a parking location. Teknomo and Hokao also found that the parking location choice depends on trip purpose, further supporting the findings of Axhausen and Polak (1991).

Thompson and Richardson (1998) present a parking choice model based on expected gain in utility. The main difference with this model was that unlike others that assumed the set of all parking choices was known, their model allowed for vehicles to compare the utility of parking in the current location against the likelihood that a better spot was available between their current location and the destination, without having information about the area in between.

### 2.4. Summary of literature review

Significant research has focused on car parking search in urban areas (Thompson and Richardson, 1998; Benenson et al., 2008; Dieussaert et al., 2009). However, there has been little consideration given to commercial vehicles. This is significant, as commercial vehicles parking search potentially has a very large impact on urban transportation networks. This is true for two reasons. First, commercial vehicles make up between 10% and 20% of all vehicles on the transportation network in most areas. Second, commercial vehicles park much more frequently than passenger vehicles. Passenger vehicles typically will park only once at each end of a trip, whereas commercial vehicles require parking facilities at each stop of their tour. By neglecting to consider commercial vehicles, researchers have neglected a very large piece of the urban parking puzzle. Commercial vehicle parking behaviour is also very different from that of passenger vehicles, given the much stronger incentives to reduce time spent driving to meet delivery times. The result is that commercial vehicles drivers spend less time cruising for parking, and are much more willing to park illegally. Because of this, simply applying models created for passenger vehicles to commercial vehicles is inadequate. This research aims to address this gap by focusing on commercial vehicle parking and the impact it may have on urban transportation networks.

## 3. 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.). This inventory consists of on-street parking, alleyways, alleyway loading zones, loadings bays, surface parking lots, and off-street public parking garages (Fig. 1). In August of 2010, driver interviews and truck parking counts were conducted to determine the demand for parking and loading. Freight trip demand was determined using the number of freight vehicles that were observed to park in the study area during the data collection. To estimate where this demand originated from, we used intersection counts (of freight vehicles) to distribute the total number of freight vehicles between the entrances to the study area. 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

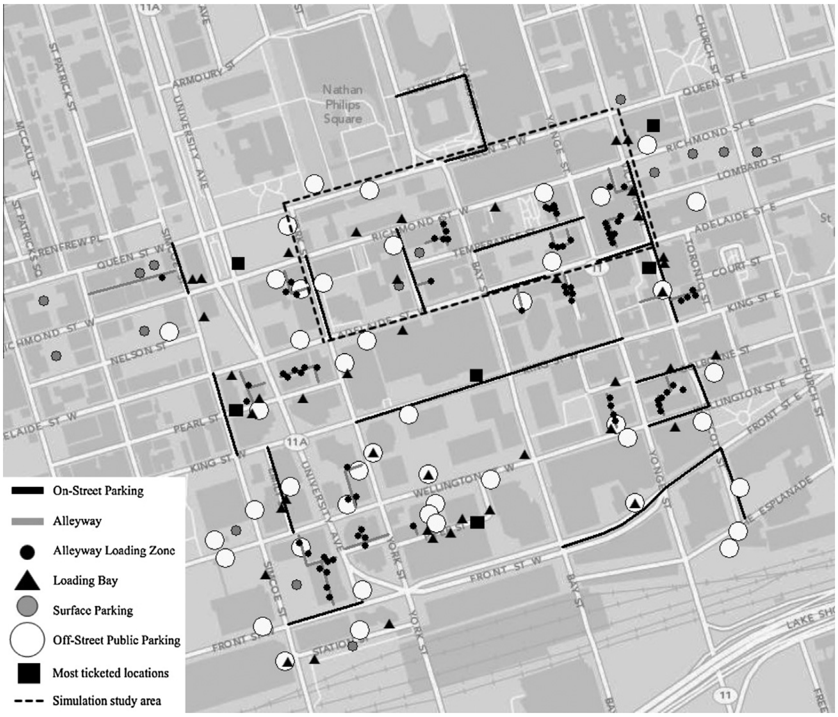


**Fig. 1.** Study area in the Toronto CBD.

representation of truck movements across the Toronto CBD. Details of the data collection effort are presented in Kwok (2010).

Fig. 1 shows the area in the Toronto CBD that was selected as the study area. The locations marked with black squares are among the ten most heavily ticketed locations in Toronto as reported by the Canadian Courier Logistics Association (CCLA). 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). 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.

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.

### 3.1. Parking choice model

The parking choice model is an econometric discrete choice model of parking spot selection. A binary logit model is developed to determine the probability of parking at a location. The alternative is to reject the location in the hope of finding a better parking spot. This model can be written as (Ben-Akiva and Lerman, 1985):

$$P_i = \frac{e^{\beta x_i}}{1 + e^{\beta x_i}} \tag{1}$$

where $\beta$ is a vector of estimated parameters and is a vector of characteristics of the current parking location $i$. The binary logit model is estimated with data from the driver interviews, in which the selected parking location was identified.

The driver interview database only included observations of parking spots that were selected. For model estimation, records for parking spots that were rejected were also required. Such records were prepared by identifying 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 estimate the driving route from the previous stop to the selected parking location. From the parking inventory, the previous two appropriate parking facilities (i.e. facilities able to accommodate the vehicle type) that the driver would have passed en route to the parking location were identified (if such facilities existed). Since no information about parking availability/occupancy at the unselected parking facilities was available, (real-time occupancy information at all locations could not be collected during the parking survey), this procedure assumed availability of parking at the unselected parking facilities. Finally, the walking distance to the delivery destination and other relevant attributes of the selected and unselected parking spots were determined.

The assumptions made in the development of the estimation dataset may have implications for the model performance. For example, drivers may have selected a route to the destination other than the shortest path in order to improve the chance of finding parking. The driver may have considered and rejected more or less than two previous parking spots en route to the selected stops. Most importantly, not all prior spots en route were necessarily unoccupied. Improving upon these assumptions would have required additional detailed information from drivers during the interviews, which would have significantly added to respondent burden.

The binary logit model for freight vehicle parking location choice is sensitive to distance from the final delivery destination and parking facility type. No additional variables are included as no data on other parking location characteristics are available. The parameters of this model were estimated using maximum likelihood estimation. The estimated parameters are summarized in Table 1.

The final model achieved a pseudo-R squared value of 0.3086. The negative coefficient on the distance term shows that the further a parking space is from the delivery destination, the less likely it is that a truck driver will choose to park there. The negative coefficient on the term representing on street parking reveals a preference against parking on street. Conversely, the positive coefficient on the term representing loading bays is positive, revealing a preference towards parking in loading bays. Other parking facilities did not enter the model as their coefficients were not statistically significant.

### 3.2. Parking simulation model

A PM peak hour parking simulation model is developed for the study area in the Paramics traffic simulation software (Quadstone Paramics Ltd.), which models vehicle movements at a microscopic level. The PM peak hour was selected based on field observations showing that this is when the greatest degree of parking activity was occurring in the simulation study area. The Toronto CBD experiences greater levels of passenger travel activity in the PM peak hour 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 locations. While truck deliveries tend to peak in the midday period (Kwok, 2010) (presumably because they are trying to avoid congestion and access receivers during staffed hours) some of the greatest parking challenges are occurring in the PM period, when parking supply is reduced on some arterial roads, congestion is heavy, and competition for parking spots (from passenger cars) begins to increase.

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 (Amirjamshidi et al., 2013). 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 through 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 250 m of its final destination. This distance threshold is evident from the parking surveys which show that no freight vehicle was parked further than 250 m away from its 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 park in the 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. The dwell time for each vehicle is calculated using Monte Carlo simulation which relies on repeated random sampling. By generating a specific dwell time (for each vehicle)

**Table 1**
Results of binary choice model for freight vehicle parking location.

| Variable | Coefficient | *t*-Stat |
|---|---|---|
| Distance to destination (m) | −6.23E−03 | −3.87 |
| On street parking facility | −1.61 | −4.11 |
| Loading bay parking facility | 2.21 | 2.09 |
| Constant | 2.12 | 6.09 |
| Log likelihood | −84.35 | |
| Pseudo *R*-squared | 0.3086 | |

from a given cumulative distribution function and repeating the same process for many vehicles, the probabilities of the generated dwell times will approximate the observed data probabilities.

The cumulative percentage distribution function (CDF) of dwell time is calculated based on a curve fit to the observed data. This function is equal to $f(x) = 0.183 \times \exp(6.045 \times x^{0.38})$, where $x$ is a random variable between 0 and 1. Setting $x$ to 1 makes $f(x)$ equal 77 min which is the maximum dwell time in the observed data. When we randomly select $x$ (between 0 and 1) and generate a dwell time for many vehicles, the pdf of the generated dwell times will be similar to the pdf of the observed data dwell times.

Fig. 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 250 m 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.

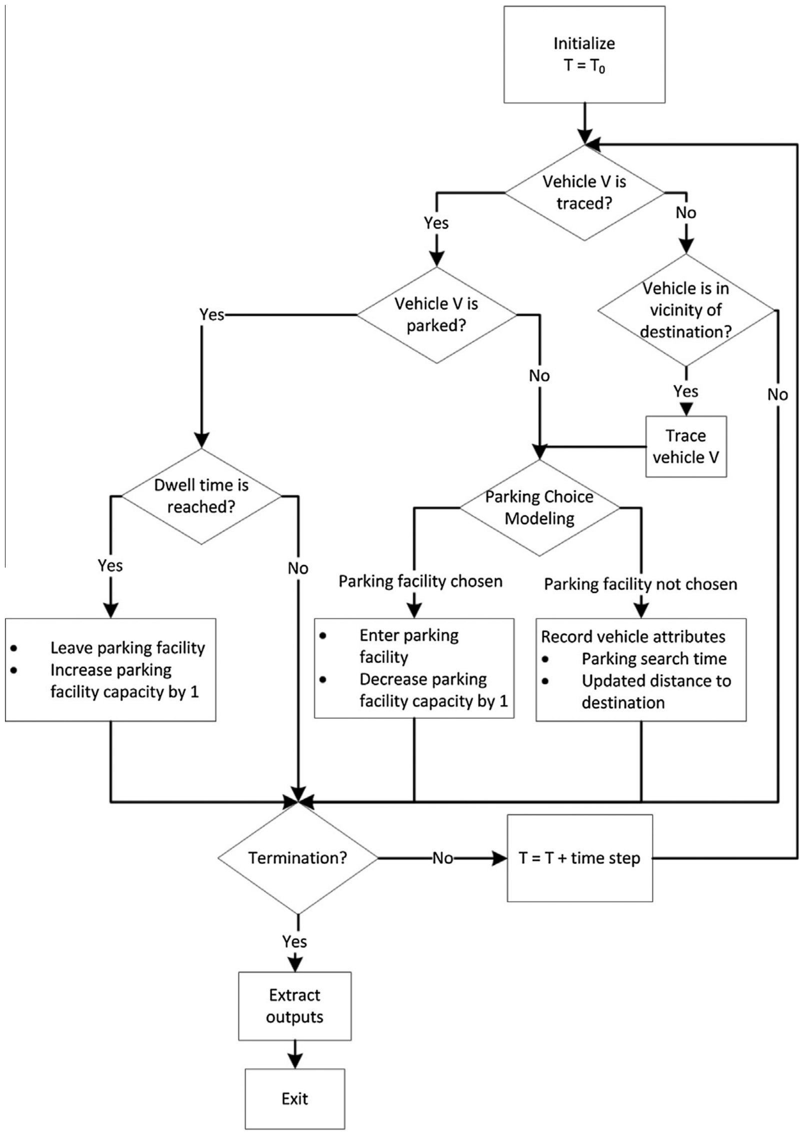


**Fig. 2.** Parking simulation model flowchart.

6. The model terminates when time reaches the simulation duration which is set to 1.5 h in this study with 0.5 h of warmup. The warmup period leads to a preload at the parking facilities.

Four measures of effectiveness calculated in the model are average search time, average walking distance, average access time, and total network travel time. 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. Total network travel time (measured in minutes) is the sum of the travel time of all vehicles in the simulation starting from the moment a vehicle enters the study area and ending at the moment it exits. This does not include the dwell time of each vehicle because parked vehicles do not contribute to the congestion of the network. Finally, average access time is the summation of search time and walking time. This measure has been introduced to evaluate cases where vehicles park far from their destinations with a search time of zero but still have to walk from their parking location to their destination.

## 4. 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 (Fig. 3a).

*Scenario 2*:

Sheppard and Temperance Streets are designated as access streets where access to parking facilities is given only to freight vehicles. Freight vehicles are permitted, however, to park elsewhere in the study area (Fig. 3b).

The results of the Scenarios 1 and 2 are compared to the Base Scenario representing the existing parking policy which allows parking of freight and passenger vehicles on all streets of the study area. To account for random variation in the model, 30 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.

Comparison of the three Scenarios shows expected differences between the search time and walking distances of both passenger and commercial vehicles. Scenario 1 results in lower freight search times compared to the Base Scenario, (although the difference is not 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 due to the exclusive access granted to freight vehicles. In Scenario 2, however, mean freight vehicle search time is further reduced to 55 s, a significant reduction. This happens because those freight vehicles with destinations on THRU 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 for freight vehicles, on the other hand, are higher for Scenario 1. 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

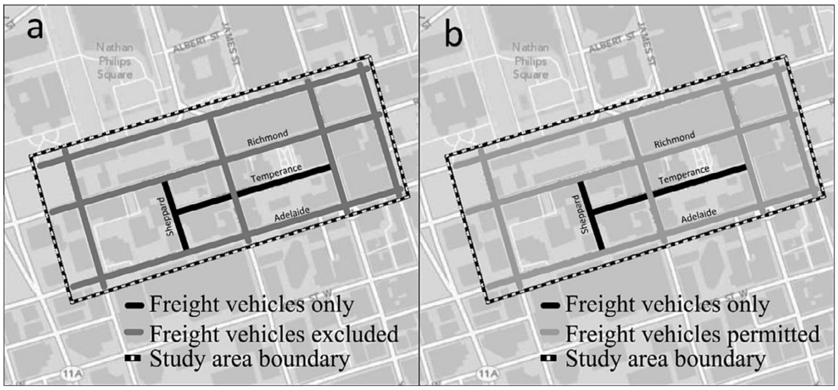


**Fig. 3.** Scenario 1 (a) and Scenario 2 (b).

**Table 2**
Comparison between base and the THRU street scenarios.

| | Search time (min) | | | | Walking distance (m) | | | | Access time (min) | | Mean of total network travel time (min) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Freight vehicles | | Passenger vehicles | | Freight vehicles | | Passenger vehicles | | Freight vehicles | Passenger vehicles | |
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | Mean | |
| Base Scenario | 2.3 | 1.27 | 1.49 | 1.34 | 71.5 | 42.6 | 84.5 | 23.2 | 3.15 | 2.50 | 3542 |
| Scenario 1 | 1.13* | 1.05 | 1.62 | 1.41 | 88.2* | 37.2 | 85.1 | 19.4 | 2.18* | 2.63 | 3497 |
| Scenario 2 | 0.92* | 0.98 | 1.74 | 1.46 | 36.8* | 32.1 | 92.3 | 24.1 | 1.36* | 2.84 | 3439 |

*Note*: changes in means are significantly different from the base Scenario with 95% degree of confidence if an asterisk follows the value.

destination. Hence, drivers have to walk further to reach their final delivery/pickup locations. The mean freight walking distance 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.

Mean access time (search time plus walking time) improves for freight vehicles, for Scenario 1, indicating that the savings in search time exceed the small additional walking time. Mean access time for Scenario 2 is less than half of that for the base scenario.

Passenger vehicles, as expected, experience different outcomes. Higher mean passenger vehicle searching time results in both Scenarios 1 and 2 (although the differences are not significant). This is due to a diversion of parking demand from the access streets to other locations where parking is harder to find. Mean walking distance also increases marginally for passenger vehicle drivers, leading to access time increases for passenger vehicles for both Scenarios 1 and 2. These increases are not statistically significant. On the whole, the results of the three Scenarios quantify an expected trade-off between measures of effectiveness of passenger and freight vehicles.

Total network travel time can be impacted in three ways. First, the cruising vehicles add to the total travel time. Second, the vehicles that are cruising for parking increase traffic volumes which lead to higher link travel times for all vehicles. Third, vehicles that park on-street decrease the capacity of the link by occupying segments of the rightmost lane. The proposed model is sensitive to the first two but not the third. The last column of Table 2 presents the mean of total network travel time which is lower in Scenarios 1 and 2 compared to the base Scenario.

## 5. 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, congestion impact, and parking 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.

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. Reductions in freight vehicle searching time occur 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 because some of their parking options are removed. 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. Third, the validity of our assumptions about parking spots that were considered but not selected could be further investigated.

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.

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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 die 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?

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