Autonomous vehicle parking policies

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Autonomous vehicle parking policies: A case study of the City of Toronto

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ABSTRACT

Autonomous Vehicles (AVs) can eliminate the burden of finding a parking spot upon arrival to the destination. AVs can park at a strategic location or cruise until summoned by their users. In this study, we investigate AV users' parking decision considering their cost and time constraints. Each users' decision has impacts on congestion which can change feasible options of other users. Hence, we use an agent-based simulation model to study AV parking policies. Results show that travelers consider sending their vehicles to park at home if they have to pay to use a parking facility. Also, our analysis for downtown Toronto shows that AVs would travel on average 12 min and a maximum of 47 min to park in cheaper parking lots. We also find that assigning the same parking price across all the parking facilities would exacerbate the congestion by motiving more AVs to cruise instead of choosing the closest parking lot. However, we show that a toll for zero-occupant AVs leads to a tradeoff between parking cost and distance that would decrease the VKT by 3.5% in downtown Toronto.

1. Introduction

One inconvenient part of auto travel is finding a spot near the destination to park the vehicle. Empirical evidence shows that travelers spend an average of 20 min to find a parking space in metropolitan areas (Chester et al., 2011). This parking search process is not only frustrating to drivers, but it also works against city planners' efforts to minimize congestion. The limited parking space causes travelers to start searching when they get close to their final destination and cruise until finding a spot. The travelers who search for parking account for approximately 30% of traffic on major streets (Shoup, 2006).

Limited and expensive real-estate motivates city planners and researchers to investigate policies to balance parking supply and demand such as dynamic parking pricing (Polycarpou et al., 2013; Glasnapp et al., 2014; Zakharenko, 2016b; Zheng and Geroliminis, 2016), and parking permits or reservations (Rosenfield et al., 2016; Lei and Ouyang, 2017). These policies influence parking decisions via the parking fee, search time, and egress time to final destination. In the near future, *Autonomous Vehicle* (AV) users will be able to exit their vehicles at their final destinations, and send their occupant-free AVs to access remote parking spots or to cruise nearby waiting for the user to complete their activity. This feature reduces parking search and egress time, and changes the balance between parking supply and demand.

The self-parking capability of AVs not only can increase parking supply, by stacking AVs behind each other inside car-parks (Nourinejad et al., 2018), but also provides more parking alternatives that change parking demand. We analyze three parking alternatives available to AV users. One alternative is that AVs may drive to a nearby parking spot and park there until they are

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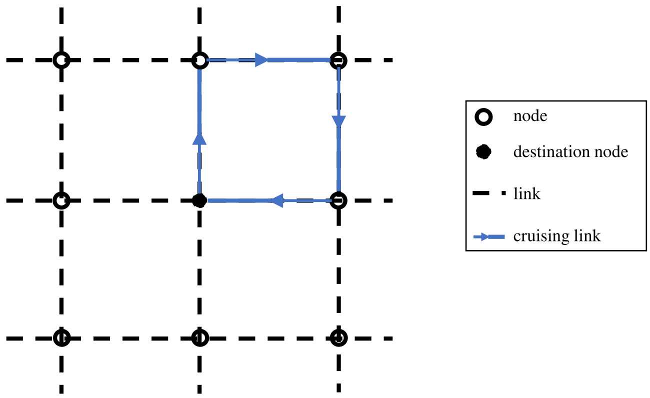


Fig. 1. An example of a cruising path around destination.

summoned by their users. While this alternative has the lowest occupant-free travel distance and consequently lowest congestion and emissions, it might not be the most economical one because the travelers have to pay the parking fee. Another alternative is that AVs may drive all the way back to the travelers' home or wherever there is free parking. One more alternative is that AVs may cruise for the whole activity time. This form of cruising is different in nature than cruising by human-driven vehicles to find a parking spot. Currently, human-driven vehicles start cruising when they approach the destination to find a parking spot. This cruising time to find parking, also known as parking search time, happens near the destination and usually is short. The existing literature on parking for human-driven vehicles has considered a fixed parking search time (Shoup, 2006) or has considered parking search time as a function of average parking search distance (Zheng and Geroliminis, 2016; Liu and Geroliminis, 2016) or parking occupancy in the area (Lam et al., 2006; Qian and Rajagopal, 2014). However, occupant-free AVs can cruise instead of parking for the whole activity time of its user. The second two alternatives (parking at home and cruising) might be more economical because the travelers do not pay for the parking, however, they exacerbate congestion and air pollution. These alternatives eliminate the burden of parking from AV users, however, they will challenge city planners' quest to reduce congestion and air pollution. This study presents a model to evaluate the impact of various policies on AV parking choices in a network context. We only focus on private use of AVs and ignore mobility as a service usage because such AVs will drive to another customer after dropping off their current passenger.

The remainder of this paper is organized as follows. Section 2 presents the existing literature and the research gap this study tries to fill. Section 3 presents the simulation characteristics and the model specification. Section 4 presents the simulation results and insights for proposing parking policies in a hypothetical grid-based city. Section 5 examines the real-world example of the City of Toronto. Finally, Section 6 concludes the paper.

2. Background

Shoup (2005) reports that between 8 and 74 percent of traffic in downtown areas are vehicles that are cruising for parking. Agent-based models can be used to capture the impact of these vehicles, traveler preferences in choosing a parking spot, and the effects of different parking policies.

Benenson et al. (2008) develop an agent-based simulation model to investigate residential parking when travelers return home at the end of the day. The model ignores the travel between origins and destinations, and travelers only enter the model near their destinations when they start searching for parking. This assumption enables Benenson et al. (2008) to develop a spatially explicit model that considers every parking spot. Travelers choose their parking spot based on the distance to their final destination, and the proportion of unoccupied parking spots. The model then generates the distributions of search time, walking distance, and fees paid by the travelers. Waraich and Axhausen (2012) consider the walking distance to final destination and parking price to develop a utility function for parking. The weight of each factor is found through stated preference and revealed preference choice surveys. Then, the parking model is embedded in the agent-based traffic simulation of MATSim. Waraich and Axhausen (2012) consider different transportation modes, and investigate how reducing parking supply can cause mode shift, and decrease peak hour congestion. These models and other studies concerning parking (Chou et al., 2008; Caicedo, 2010) only consider human-driven vehicles. A comprehensive review of parking search for human-driven vehicles can be found in Brooke et al. (2014).

Zhang et al. (2015) are among the first who investigate the impact of AVs on parking demand. They assume that all trips in a gridded city are served by a fleet of AVs, and investigate the impact of fleet size and ride sharing on parking demand. Since all AVs are assumed to be shared, and AVs park or cruise until they find the next passenger, they ignore the possibility of parking at home, as well as impact of parking pricing and other policies. In another study, Nourinejad and Amirgholy (2018) present an equilibrium model to find the parking location of AV commuter trips over a linear city network. Since the model only considers commuter trips with long activity times, Nourinejad and Amirgholy (2018) ignore the option of cruising for the whole dwelling period.

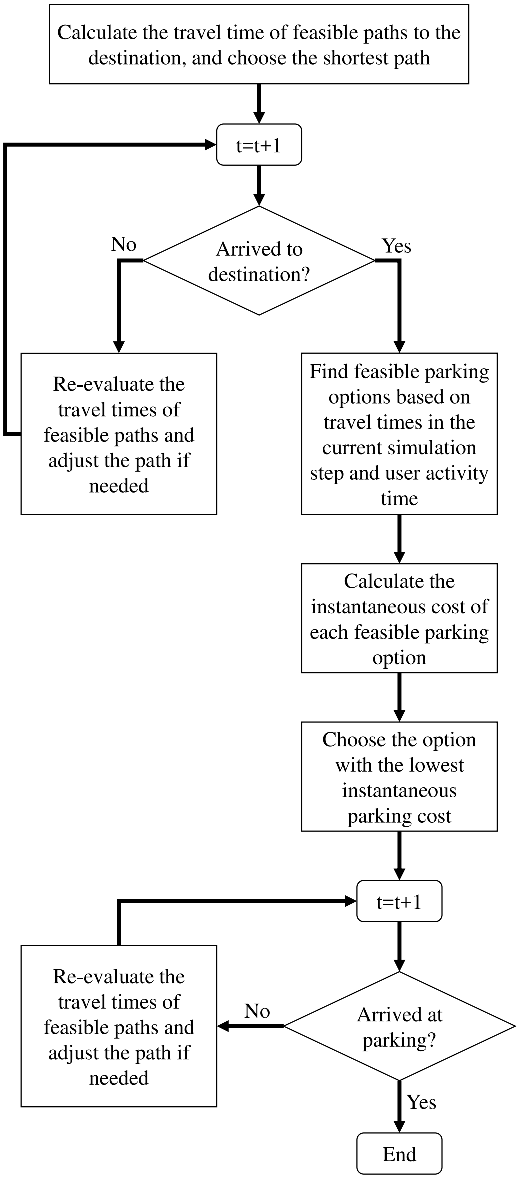
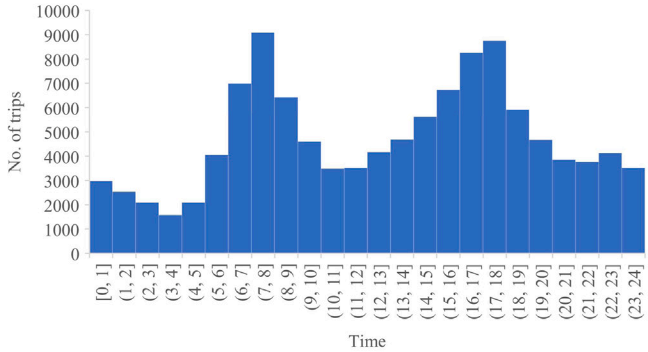


Fig. 2. Individual agent actions in the agent-based simulation model.

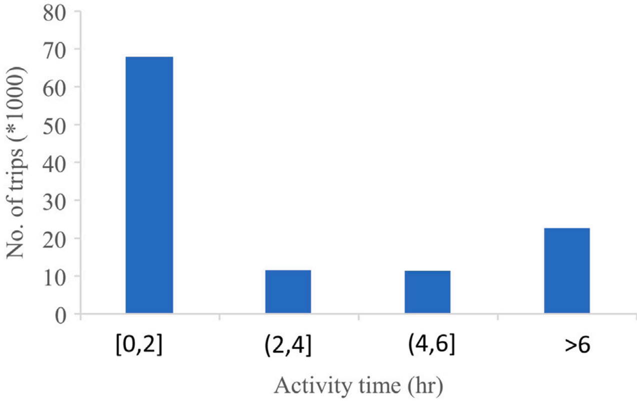
Zhang et al. (2019b) present an equilibrium model of the choice of parking locations for commuter trips by AVs over a linear city under Vickrey's single-bottleneck setting (Vickrey, 1973). This model only considers commuter trips with long dwell times, which enables them to ignore the option of cruising for parking. Zhang et al. (2019a) investigate the joint problem of parking choice and traffic assignment for AVs. This study also does not consider the option of cruising instead of parking and AVs only choose among available parking facilities based on travel cost from destination to the parking facility and parking fee at the parking facility.

Zakharenko (2016a) investigates the daytime parking location of AVs in a mono-centric two-dimensional city with a half-circular shape. Zakharenko (2016a) considers three options of parking near the workplace, parking at a farther special parking zone, and parking at residential lots. The analysis shows that 97% of commuter AVs park in the dedicated parking zones, and the optimal location of such zones is just outside of the commuter work zone. Zakharenko (2016a) suggest that no congestion pricing should be applied to zero-occupant AVs because otherwise they will choose the central parking spots and decrease social welfare.

Harper et al. (2018) investigate the parking location of AVs in the City of Seattle using an agent-based simulation model. They model the agents as zero-occupant AVs which start searching for the cheapest parking lot in downtown Seattle, and do not consider the traffic flow, congestion, and other parking choices. Their analysis shows that AVs will travel farther for free or cheaper parking which will increase the Vehicle-Kilometer Traveled (VKT) by 2.5% in Seattle. This feature will decrease parking lot income and might make them economically unsustainable.



(a) Trip departure time distribution histogram.



(b) Activity time at destination distribution histogram.

Fig. 3. Characteristics of randomly generated trips.

Millard-Ball (2019) considers cruising instead of parking as an option and investigates the parking choice of AVs in downtown San Francisco. He assumes two scenarios of high ($1.98/h) and low ($0.29/h) cruising cost. Millard-Ball (2019) also assumes that AVs can collaborate with each other and choose the most congested cruising path to cause gridlock to decrease their cruising cost. The analysis shows that 6% of AVs cruise in high cruising cost while near 50% will cruise in low cruising cost. However, Millard-Ball (2019) considers that the travel time between parking lots and destinations are fixed. Also, Millard-Ball (2019) assumes that the cruising AVs can return to pick up the passenger immediately. The assumption of fixed travel time between origin and destination may lead AVs to choose a parking lot that is unreachable due to congestion. Similarly, the assumption of immediate arrival of the cruising vehicle to pick up location encourages AVs to enter the gridlock to decrease their cruising speed and cost without considering the challenge of reaching the user on time.

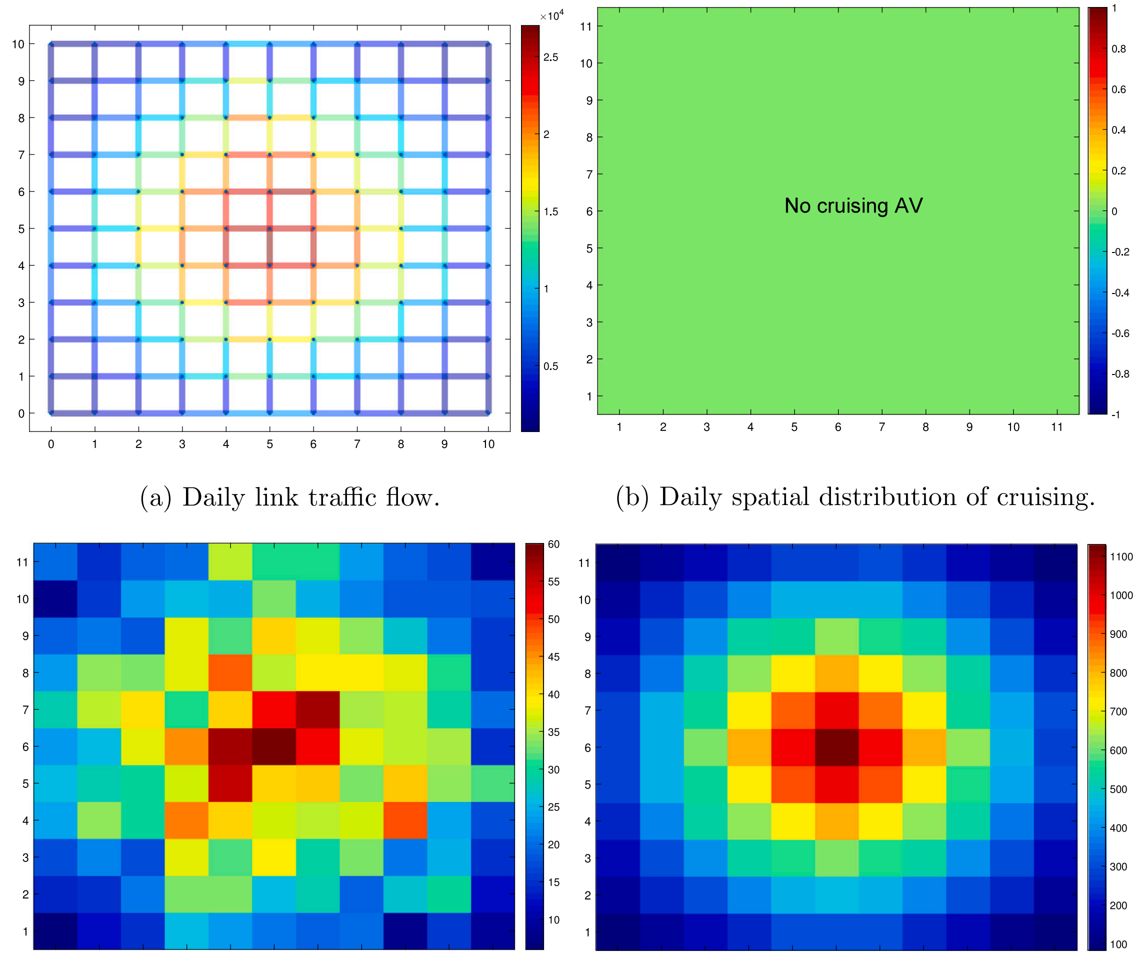
Bahrami et al. (2021) develop a static framework to investigate the parking choice of privately-owned AVs with different users' activity time duration in a downtown area. They consider a steady state condition in which the cost of different parking options and congestion do not evolve.

To fill these research gaps, we evaluate the impact of parking policies on AVs using an agent-based simulation model. The simulation model enables us to investigate whether AVs park or cruise, and their parking location if one exists. We also assess the parking and occupant-free congestion pricing fee impact on parking choice and congestion. We only consider the private ownership of AVs, and disregard the mobility as a service usage. If AVs are used as mobility-as-a-service, they will drive to the next customer or cruise until finding her instead of parking.

3. Model specification

AV users make parking decisions when they reach their destinations. Now, we present the cost of three aforementioned parking alternatives: *(i)* park in a parking lot, *(ii)* park at home, and *(iii)* cruise instead of parking. Consider parking lot p located t_p hours from a traveler's destination that costs $\$r_p$/h to park. The total cost for an AV to park at parking lot p is

$$C_p = 2t_p c_d + r_p(t - 2t_p), \tag{1}$$



(a) Daily link traffic flow.

(b) Daily spatial distribution of cruising.

(c) Daily spatial distribution of parking at parking lots.

(d) Daily spatial distribution of parking at homes.

Fig. 4. Base case scenario with $r_p = 3[\$/\mathrm{h}]$ and $c_d = 12[\$/\mathrm{h}]$.

where c_d is the travel cost per hour of an occupant-free AV. This cost can consist of fuel and congestion pricing toll. The coefficient 2 accounts for the round trip from destination to the parking facility and back. Also, t is the activity time in hours. The parking duration is the activity time minus the round trip travel time from the destination to the parking facility. Hence, the first term in the right-hand side is the travel cost and the second term is the facility usage cost.

Similarly, the total cost of an AV that returns and parks at home located t_h hours from the destination to save the parking fee is

$$C_h = 2t_h c_d. \tag{2}$$

Finally, the total cost of cruising around the block for the whole activity time is

$$C_c = c_d t. \tag{3}$$

Parking at home or at a parking lot is only feasible if the activity time is more than the travel time of the round trip from the destination to the final parking location. Otherwise, the AV cannot reach to the parking location. Hence, parking at home is a viable alternative only if:

$$t \geq \alpha(2t_h), \tag{4}$$

where α is the confidence factor. The confidence factor considers the variation in travel time and risk aversion of travelers regarding this variation because the travel time depends on parking choices of all travelers. For instance, if the round trip from a destination

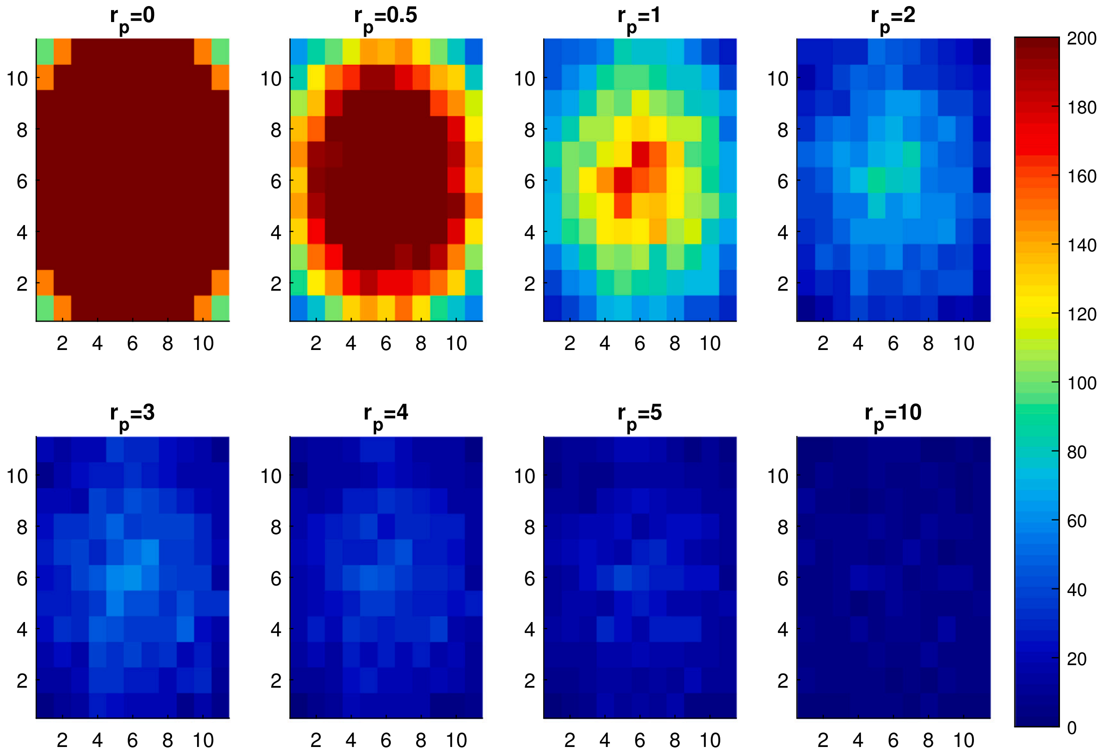


Fig. 5. Daily spatial distribution of parking at parking lots for different parking hourly costs.

to home takes 50 min, and the confidence factor is 1.2, the traveler considers sending the vehicle to park at home only if the activity time is more than 60 min. Similar constraint applies to round trips to parking lots, and an AV can choose a parking lot only if the round trip to that parking lot multiplied by confidence factor is less than the activity time:

$$t \geq \alpha(2t_p). \tag{5}$$

We assume that if the AV chooses to cruise for the whole activity time, it would choose one direction randomly and travel around the block in that direction. Such behavior enables users to summon their AVs quickly, and makes cruising a promising alternative for short activities. Fig. 1 shows that an AV chooses to cruise in north east loop.

If the number of cruising AVs increases on some links, those links would become more congested and their travel times may increase. The increased travel time of these links increases the round-trip travel time from destination to home and some parking facilities which may prevent AVs from returning on time to pick up their users if they park at these locations. We check these situations in constraints 4 and 5 to ensure that users can only send their AVs to home or a parking lot if the round-trip travel time to these locations is less than users' activity time at their destinations.

The model simulates all auto trips within a city and assigns them to the network based on Wardrop equilibrium. When each user arrives at her destination, the model considers all feasible parking options based on travel times in the current simulation time step, which is 1 min, and the user activity time. Then each user chooses the parking option with the lowest instantaneous cost and follows the shortest travel time path between the destination and parking location. Although a user cannot change the parking decision after being dropped off, the vehicle can adjust its path to parking location by re-evaluating the path travel times and adjusting the shortest path during its travel towards the parking location. Fig. 2 shows the step-by-step approach of our simulation model. Our model is an agent-based simulation that considers each user individually and checks travel time constraints to home and different parking lots at the time of making a parking decision. Hence, it endogenously captures the impact of each user's decision on congestion and the decisions of other users who make their parking decisions later. Hence, the model provides a platform to investigate the impact of different parking policies on congestion.

4. Hypothetical city

We first simulate a hypothetical grid-based city. Our purpose of presenting a hypothetical city is to capture the impacts of different policies in a simple and tractable case. We now describe the characteristics of the simulated city and its population. The characteristics of this city are similar to those in Zhang et al. (2015). Our hypothetical city is 10 km × 10 km, and lies on a grid network with block length of 1 km. The population density is 2500 people per square kilometer in the center node

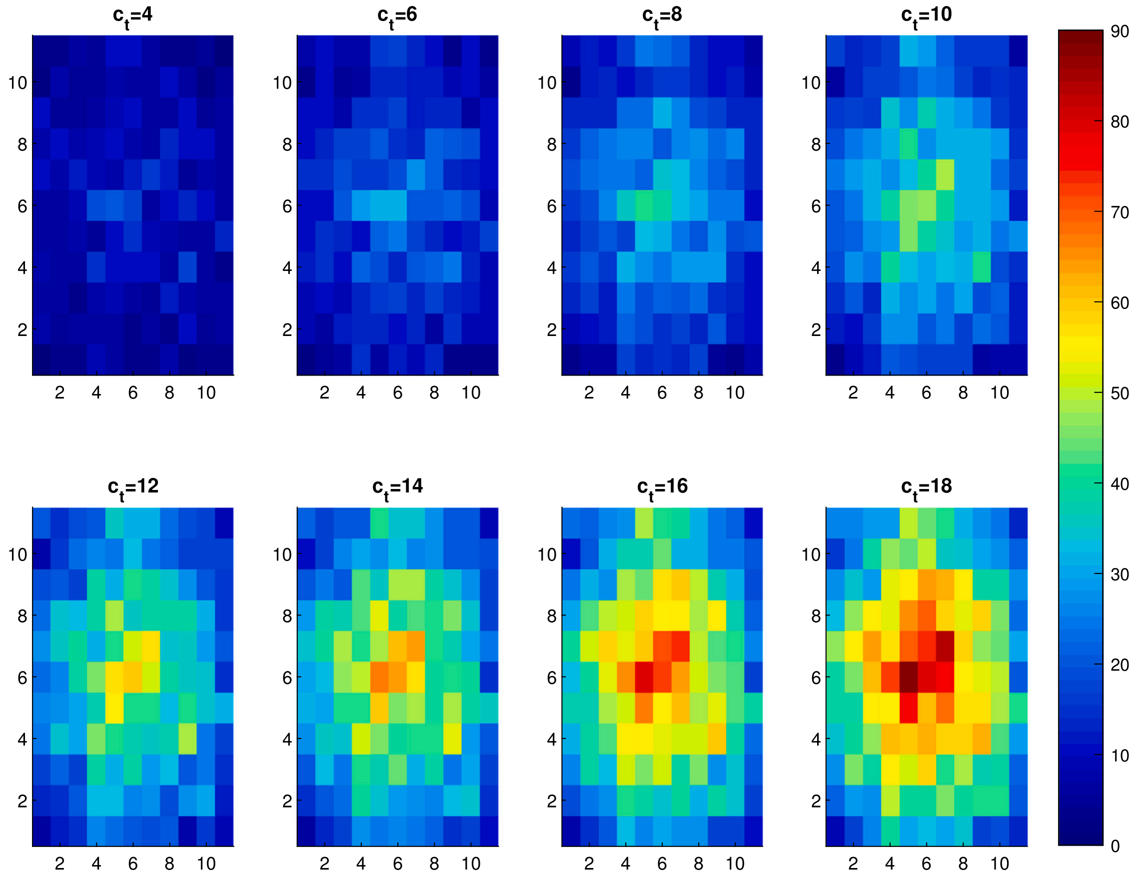


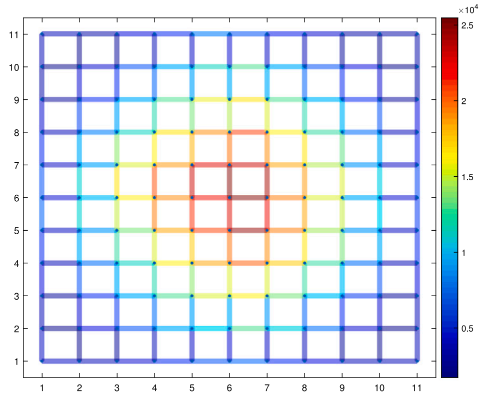
Fig. 6. Daily spatial distribution of parking at parking lots for different travel cost.

of this city, and 300 people per square kilometer in four corner nodes. The population of other nodes varies linearly between these values based on their Euclidean distance from the center. We assume that each traveler generates 3.8 auto-trips per day on average. We assume that these trips are distributed based on a gravity model with travel cost equal to 5 times the Euclidean distance between origin and destination. Trip departure times and activity times at destinations are randomly generated. Fig. 3(a) shows the assumed departure time distribution histogram. It does not include the parking trips. The activity time is assumed to follow a truncated normal distribution between 0 and 10 h, and is shown in Fig. 3(b). Each link's capacity and the free flow speed are set at 3000 vehicles per hour and 60 km per hour, respectively. The volume-delay function follows the BPR equation (travel time = free flow travel time$(1+0.15(\frac{\text{volume}}{\text{capacity}})^4)$). The simulation time step is 1 min which means that every variable is updated every minute. Hence, the shortest path of each user is re-evaluated at each time step and updated if necessary.

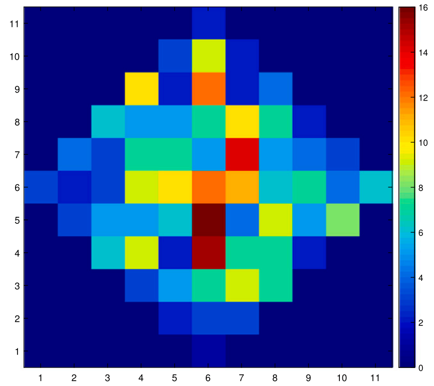
In the base scenario, it is assumed that there is a parking lot at each node, where it costs \$3/h to park. Also, it is assumed that AVs do not pay any congestion pricing toll, and the travel cost only accounts for fuel cost and is \$12/h. The confidence factor for sending the car back home is 1.2. Fig. 4 shows the results. First, Fig. 4(b) shows that no vehicles cruise instead of parking in this case. Comparing Figs. 4(a) and 4(d) shows that sending vehicles back home to park causes congestion, and the link flows are higher in the vicinity of populated areas. Fig. 4(c) shows that the maximum daily parking demand is 60 vehicles, and it is demanded in the center which is the destination of most trips. Fig. 4(c) is not symmetrical because the activity time of travelers varies randomly. In the base scenario, 3476 travelers park, their average activity time is 28.8 min, and they pay \$5013.5 for parking. 53,256 travelers send their AVs to wait at home, and their average activity time is 317.1 min. Fig. 4(d) is donut-shaped because the number of trip origins and destinations decreases linearly from the center. Also, the high number of travelers using their homes for parking normalize the activity time impact. The total vehicle kilometers traveled (VKT) is 971,682. Results show that it is more economical for travelers with a longer activity time to send their AVs back home, even though the parking cost is only \$3/h.

4.1. Parking cost sensitivity analysis

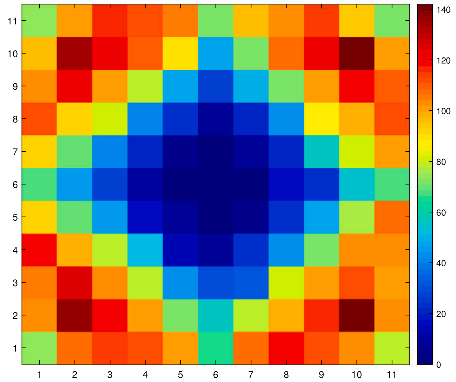
To promote using parking lots and decreasing the VKT, either the parking price should be decreased or a congestion toll for zero-occupant AV trips should be imposed. Hence, a sensitivity analysis on parking price is performed. Table 1 and Fig. 5 show the results for parking cost sensitivity analysis. Results show that when free parking is available all AVs use parking lots and the



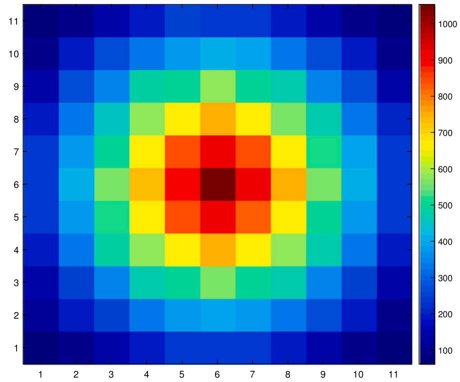
(a) Daily link traffic flow.



(b) Daily spatial distribution of cruising.



(c) Daily spatial distribution of parking at parking lots.



(d) Daily spatial distribution of parking at homes.

Fig. 7. The scenario of having four parking lots in the four corners.

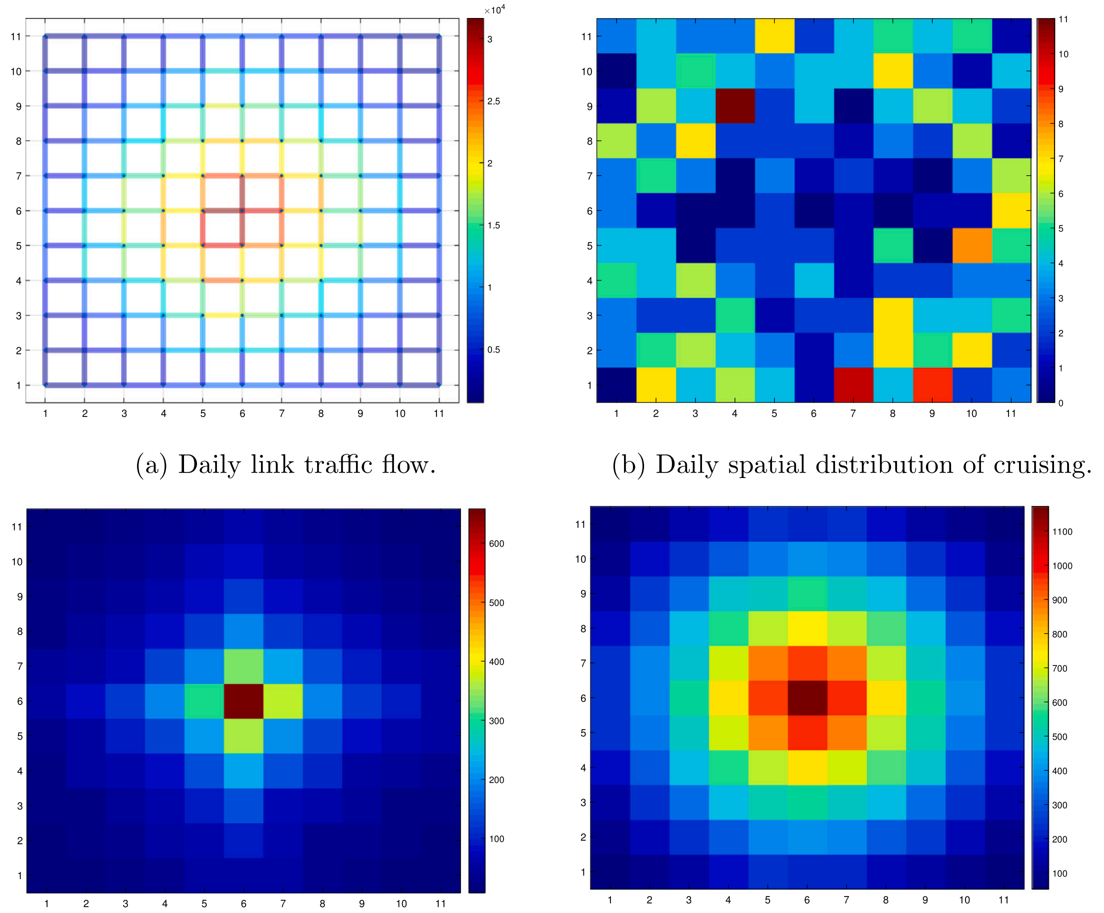
Table 1
Parking cost sensitivity analysis.

Hourly parking cost ($/h)	VKT	% increase relative to free parking	Total collected parking fee ($)
0	531,682	–	0
0.3	641,383	20.63	35,690.3
0.5	749,035	41.05	27,807.5
1	877,733	65.28	14,433.1
2	946,875	78.30	7,278.9
3	971,682	82.97	5,013.5
4	981,881	84.89	3,857.3
5	990,046	86.43	2,961.1
10	1,005,030	89.25	1,528.7

total VKT is 531,682. However, when parking lots charge even as low as $0.5/h some travelers send their vehicle to park at home, which increases the VKT by approximately 40%. Results show that if the hourly parking cost increases, more AVs would be parked at home and the VKT increases, consequently. Results also show that the total parking income decreases when the parking hourly cost increases. Results show that the highest parking income is $35,690 and it happens when the hourly parking cost is $0.3/h.

4.2. Travel cost sensitivity analysis

The travel cost of AVs depends on fuel cost, and tolling price. For instance, if AVs are powered by electricity, their travel cost per hour will decrease. Also, if a congestion toll is applied to zero-occupant AV trips, their travel cost will increase. Hence, it is



(a) Daily link traffic flow.

(b) Daily spatial distribution of cruising.

(c) Daily spatial distribution of parking at parking lots.

(d) Daily spatial distribution of parking at homes.

Fig. 8. The scenario of having one parking lot in the center.

important to perform sensitivity analysis on travel cost. We fix the parking cost at $3/h, run our model for different travel costs, and show the results in Fig. 6. Fig. 6 shows that fewer AVs would be parked at parking lots if the travel cost decreases. The VKT decreases from 1,002,702 at c_d = $4/h to 946,875 at c_d = $18/h. It is logical because more AVs park at their destination rather than going home. The results alongside with parking cost analysis show that AVs will not cruise if the parking cost is less than travel cost. It happens because it is assumed that there is enough parking capacity at each node. This assumption is relaxed in the next subsection.

4.3. Parking location analysis

In this section, we vary the location of parking lots, while the parking cost and the travel cost are fixed at $0.3/h and $12/h, respectively. First, four parking lots are considered at the four corners. Fig. 7(b) shows that no vehicles cruise near the corners where the parking lots are located, and the number of cruising vehicles increases with the distance from the parking lots towards the center. Similarly, Fig. 7(c) shows that the vehicles close to the corners use the parking lots, and the vehicles in the center do not use the parking lots. The total parking income is $9,403 per day. Figs. 7(a) and 7(d) show that the vehicles in the center use their homes as the parking lot and the congestion in that area is consequently higher. The total VKT is 860,796.

Then only one parking lot is located in the center of the city. Fig. 8 shows the result of this scenario. Fig. 8(b) shows that more vehicles cruise instead of parking in comparison to the previous scenario and they are distributed all over the city. Also, Fig. 8(c) shows that the parking lot is mostly used by the vehicles in the center of the city. It happens because the congestion in the center is high and the activity time of travelers is not enough to reach the parking lot. Finally, Figs. 8(a) and 8(d) show that most of travelers choose to park at home and the congestion is expanded over a bigger area. The total parking income and VKT are $8,585 and 872,197, respectively.

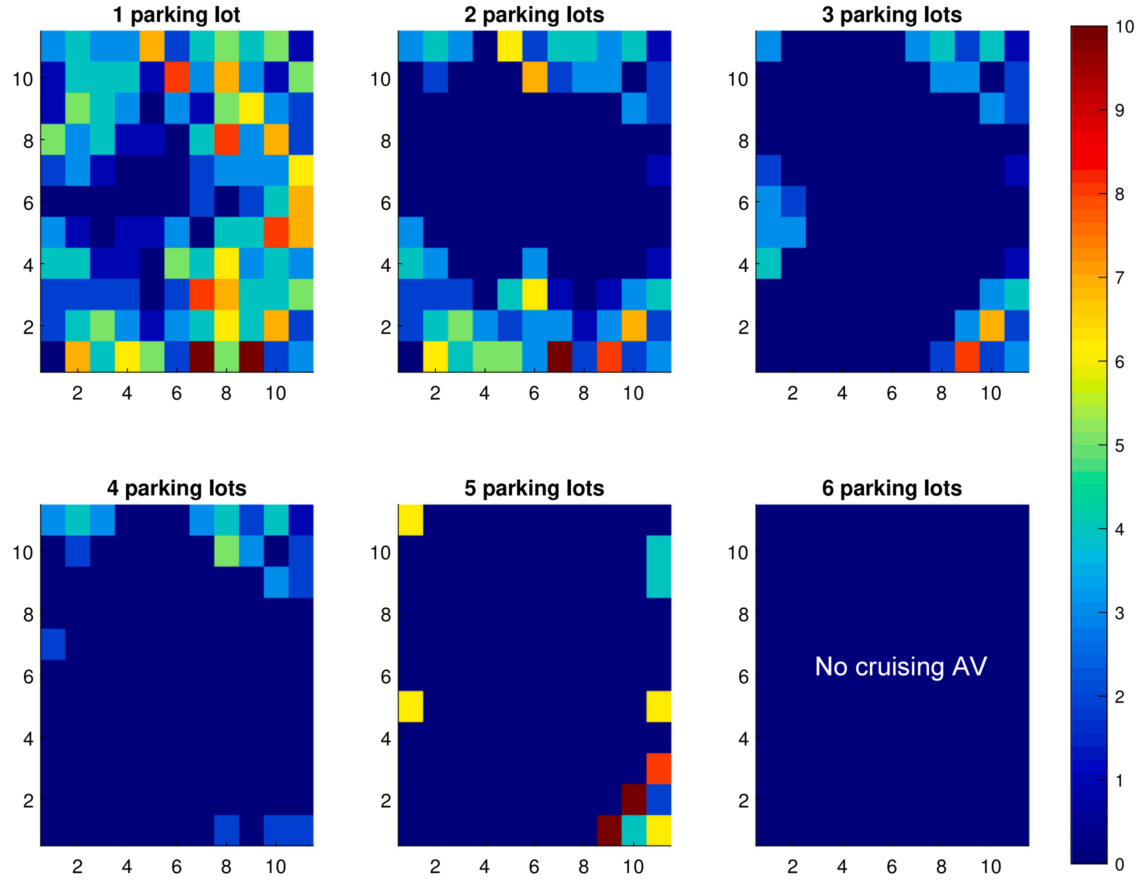


Fig. 9. Daily spatial distribution of cruising AVs for different number of parking lots.

The Simulated Annealing (SA) algorithm (Kirkpatrick et al., 1983), which is a probabilistic meta-heuristic optimization method, is used to find near optimal parking locations with the lowest VKT. SA notion comes from annealing in metallurgy, which involves heating and cooling of a material, and it is often used to find an approximation of the global optimum solution in a large and discrete state space. Van Laarhoven and Aarts (1987) show that the SA solution does not depend on the initial solution, and it can find the global optimum solution with large number of iterations. SA is used by defining the states as the location of parking lots. For each state, the agent-based simulation model is run and VKT is recorded and used in future iterations. The initial temperature of the SA algorithm is set to 0.05, the final temperature is set to 0.001, the cooling function is $T_{k+1} = gT_k$ where T_k is the temperature of the kth iteration and g is the cooling rate which is set to 0.85. The number of iterations in each temperature is set to $L = 10 * number\, of\, parking\, lots$. The steps of the SA algorithm are as follows:

Step 1	Generate an initial set (I) of parking lots location randomly. Set the counter to one ($k = 1$).
Step 2	Repeat steps 3 to 7 for L times.
Step 3	Generate a new set (J) of parking lots locations randomly.
Step 4	Calculate $\Delta VKT_{IJ} = VKT_J - VKT_I$.
Step 5	if $\Delta VKT_{IJ} \leq 0$, set $I = J$ and go to step 7.
Step 6	Generate a random number in the interval of $[0, 1)$. If $exp(\frac{\Delta VKT_{IJ}}{T_k * 10^5})$ is greater than the generated random number, set $I = J$ and go to step 7.
Step 7	Set $k = k + 1$.
Step 8	Decrease the temperature ($T_{k+1} = gT_k$). If the temperature is greater than the final temperature go to step 2.

Table 2 and Fig. 9 present the results of SA algorithm. Results show that as the number of parking lots increases the VKT decreases because more AVs use parking facilities. Also, Fig. 9 shows that no AVs cruise when there are 6 optimally located parking lots.

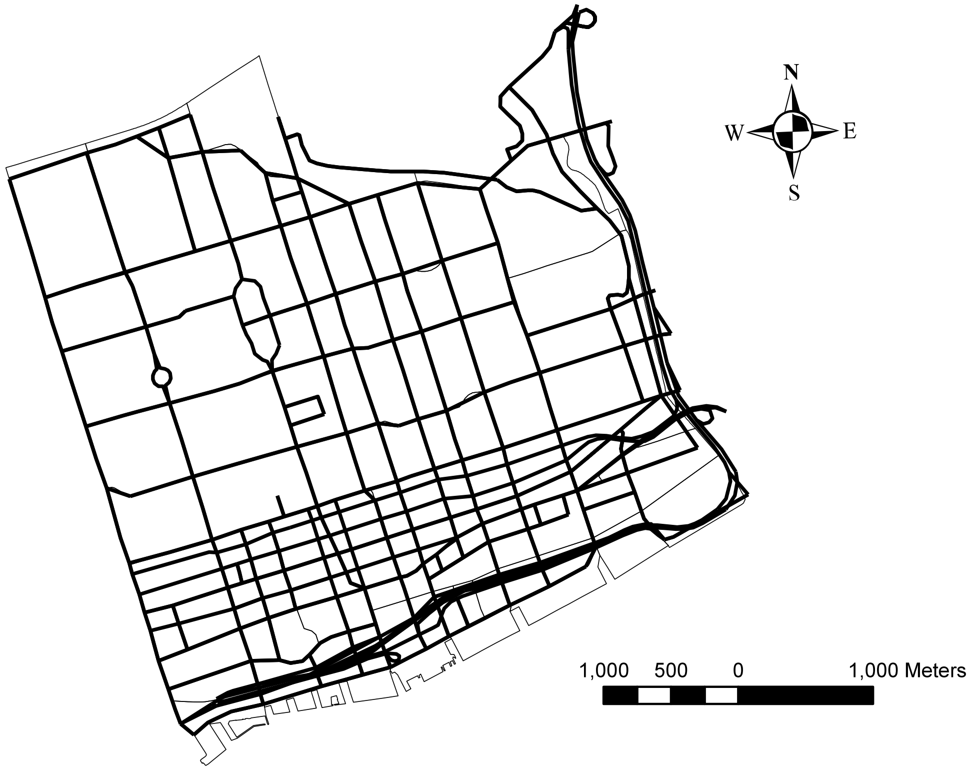


Fig. 10. Study area of downtown Toronto.

Table 2
Optimal parking locations.

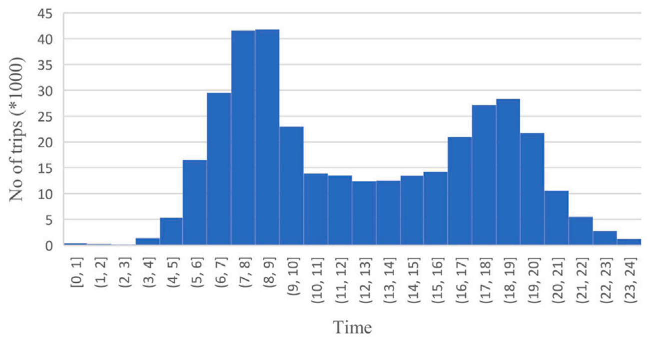
Number of parking lots	Selected locations	VKT
1	50	867,512
2	40, 83	803,254
3	35, 42, 83	777,389
4	26, 52, 59, 93	759,790
5	30, 36, 70, 77, 84	747,103
6	15, 21, 50, 58, 87, 103	736,641

Also, a sensitivity analysis on the travel time confidence factor (α) is performed. This factor considers the variation in travel time and risk aversion of travelers regarding getting their vehicles on time when sending them to a parking lot or home. However, the results do not change considerably for $1 \leq \alpha \leq 1.5$.

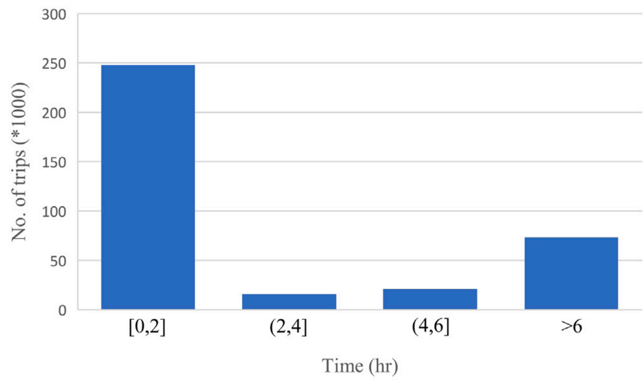
5. Real world example

The impact of AVs is examined in a real-world network of the City of Toronto. The study area is downtown Toronto which is bounded by Lake Ontario to the south, Bathurst Street to the west, the mid-town rail corridor and Rosedale Valley Road to the north and the Don River to the east. Fig. 10 shows the study area. Trips originating from or destined to the study area are provided by GTAModel V4.0, which is the latest operational travel demand model developed by the Travel Modelling Group (GTAModel V4.0, 2019). The home parking option is not considered for trips that originate from outside the study area. Figs. 11(a) and 11(b) show the trip departure time histogram, and activity time at destination histogram. There are currently 50 parking lots in the area. Their capacities are expanded by 1.65 according to Nourinejad et al. (2018), which increase the total parking supply in the area to 47,500 spots.

First, the current pricing for each parking lot is considered. The hourly parking cost in the area varies between \$2/h and \$11/h. Also, some parking lots have a maximum daily charge which are in the range of \$6 to \$30. The travel cost is assumed to be \$12/h (CAA, 2013). Fig. 12 shows four snapshots of traffic flow in the study area. Results show that travelers will not choose cruising instead of parking if their activity time is more than 18 min. The average activity time of travelers who choose to park at home and parking lots are 221 min and 319 min, respectively. This happens because the home parking option is not considered for those who live outside the study area. Results also show that AVs travel on average 12 min to access the parking lots. The analysis



(a) Departure time distribution histogram.



(b) Activity time at destination distribution.

Fig. 11. Characteristics of trips in the study area of downtown Toronto based on GTAModel V4.0.

shows that the parking lots with an hourly rate more than $6/h, which are located in the heart of business district, would not be used under current pricing, and AVs would travel up to 47 min for cheaper parking spots. The AVs would pay around $1 million for parking fees per day, and the total daily VKT in the study area is 1,558,657.

In order to use all parking lots and decrease the VKT, either an equal parking fee or a toll for zero-occupant AVs can be considered. First, an equal hourly parking fee of $5/h with maximum daily charge of $30 is considered. Under this scenario, all parking lots would be used and AVs pay approximately $3.5 million for parking. Also, the average access time to parking lots would decrease to 10 min. However, the total daily VKT and maximum access time to parking lots would increase by less than 1%. These happen due to the fact that more AVs would cruise instead of parking when the parking cost increases, and travelers find cruising as the most economical option up to 30 min activity time.

A toll of $5/h for zero-occupant AVs travel in the study area is also considered. Results show that the average and maximum travel time to parking lots is 11.5 min and 43 min, respectively. The most expensive parking lot in the study area with the hourly rate of $11/h would not be used by travelers. Also, the maximum activity time of travelers who send their AV to cruise around their destination is 18 min. The zero-occupant travel toll would decrease the total daily VKT by 3.5%, and travelers pay $212,072 per day for the zero-occupant travel toll.

6. Conclusion

AVs will change traveler reaction to parking policies by means of their self parking capability. This feature enables AV users to send their vehicle to cruise around the block or travel back home instead of parking at a parking lot. In this paper, AV parking patterns are investigated in a network using an agent-based simulation model. It is assumed that each traveler would minimize her parking cost while considering her time limit. Results show that travelers consider parking at home or cruising instead of parking at parking lots if they have to pay anything for parking. The case study of downtown Toronto shows that AVs would travel on average 12 min to access a parking lot. Also, the self parking capability of AVs enables them to travel up to 40 min to park in a cheaper parking lot, and makes expensive parking lots economically unsustainable. While applying the same parking fee at all parking lots may promote cruising for longer activity times, the zero-occupant travel toll decreases the daily VKT. Even though the results are presented for the case study of the City of Toronto, they can be generalized to downtown of other cities in the age of AVs as parking pricing and provision have similar attributes in downtown areas of many cities.

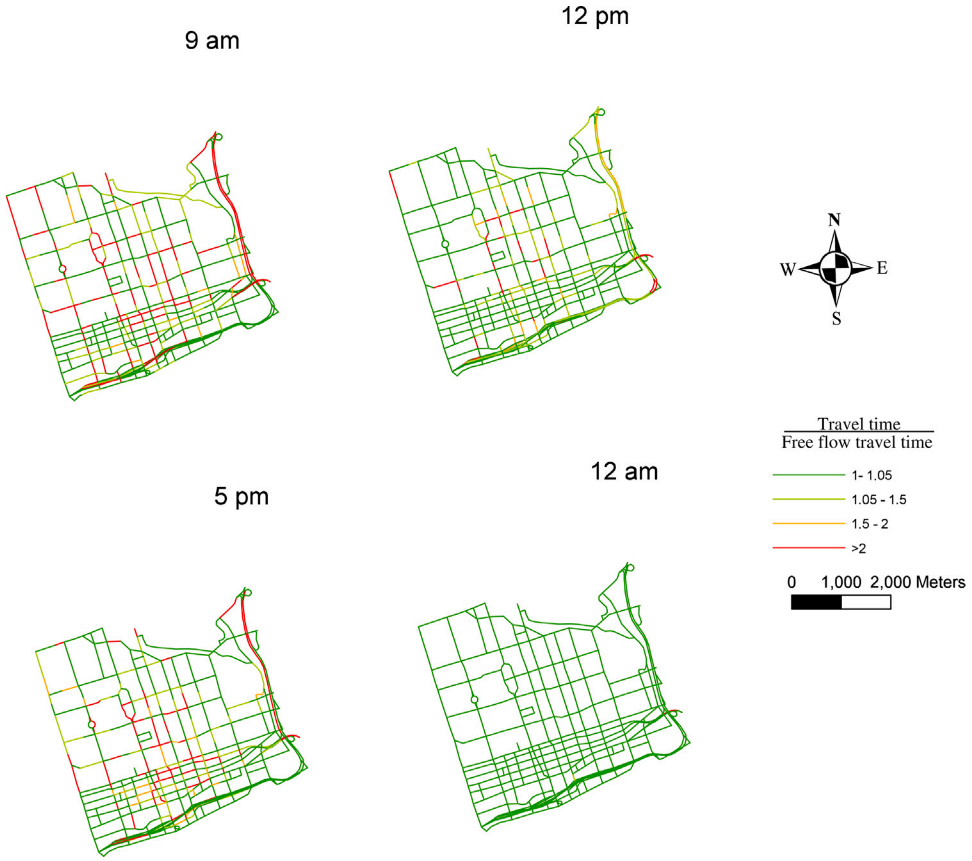


Fig. 12. Traffic flow in downtown Toronto.

In this paper, only the private usage of AVs is considered, and the mobility as a service is not considered. Also, the possibility of mode shift with respect to parking policy changes is not considered. In a future study, the simulation model can be integrated with a mode choice model to consider such options. In this paper, we also assume that AV users make deterministic parking decisions only based on the cost. A discrete choice modeling approach could also be tested if appropriate revealed preference or stated preference data on AV parking choices could be obtained. Other considerations could be incorporated such as a preference to keep the car nearby, opportunities to send their AVs to pick up goods on their behalf, send their AVs to another family member or a friend to use it, or even rent their AVs to ride-sharing services. Based on revealed preference or stated preference survey data a more realistic parking choice model could be developed that incorporates these factors. The congestion under such a scheme might lead to different policies which should be studied further. Policymakers can use different parking management and policies such as dynamic parking pricing, parking provision, and parking reservation to achieve goals including but not limited to decreasing congestion, maximizing social welfare, or increasing public transit ridership. Another direction for future research is assessing additional parking policies and their impacts on goals s beyond congestion reduction such as social welfare maximization with extensions to this modeling approach.

CRediT authorship contribution statement

Sina Bahrami: Study conception and design, Analysis and interpretation of results, Writing – original draft. **Matthew Roorda:** Study conception and design, Writing – original draft.

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