# Simulation Modeling of Urban E-Scooter Mobility

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***Abstract*—Shared micromobility is a rapidly growing transportation technology, with several companies establishing e-bike and e-scooter programs in cities all across the globe. In this paper, we use two years of empirical data on e-scooter usage from a pilot project in the City of Calgary to create a synthetic workload model of e-scooter traffic. Using this model, we develop a simulation environment to evaluate the impacts of different e-scooter management policies (e.g., fleet size, battery re-charging strategies, and urban parking infrastructure locations) on the efficacy of the e-scooter system. Our simulation results highlight the importance of proper site selection for parking areas and battery charging infrastructure.**

***Index Terms*—Shared micromobility; Simulation modeling; System design and optimization**

## I. Introduction

In the past few years, bikes and scooters available for short-term rental have been deployed in cities all over the world as part of a paradigm shift in transportation towards shared mobility. As the global population becomes more urbanized, city planners are faced with the challenge of maintaining efficient and accessible transportation options in increasingly dense population centers. Shared vehicles play a key role in sustainable cities, and the market for these services has continued to grow rapidly since their introduction.

Shared mobility programs can offer many benefits in an urban setting. These include reducing reliance on personal vehicles, ameliorating traffic congestion, and making public transit more accessible by providing first-mile/last-mile access to major transit stations. Furthermore, the flexibility, novelty, and low cost of this transportation option make them appealing both for commute (e.g., work, school) and non-commute (e.g. leisure, sight-seeing, social outings) trips.

Nonetheless, implementing an urban shared micromobility program has its own set of challenges. From a user point of view, issues include consumer adoption, cost, ease of use, safety, and pandemic-related considerations. From the city's perspective, challenges include infrastructure requirements (e.g., pathways, parking, re-charging stations), management policies (e.g., rider rules, sidewalk use, vendor selection, clutter from improperly parked scooters [15]), road safety (i.e., speed limits, interactions with cars, bikes and pedestrians), and sustainability. From a vendor's point of view, challenges include operating costs and profitability (e.g., fleet size, pricing, battery re-charging strategies, revenue/cost sharing agreements).

These challenges are novel and involve multiple perspectives. Although ride-sharing and car-sharing programs have similar issues, and have existed around the world for quite some time, the current trend towards bike-sharing and scooter-sharing programs is quite recent. As such, there are relatively few studies on shared micromobility programs that might inform research and/or policy on these issues.

This paper aims to address some of these challenges, using the City of Calgary as a case study. In 2018, the City of Calgary announced a two-year pilot program for shared micromobility using e-bikes and e-scooters. Following the pilot study, the City released an open dataset to the public that included trip data for almost half a million e-bike and e-scooter trips for the years 2019 and 2020. The empirical data showed far greater usage for e-scooters than for e-bikes, and sustained growth in usage even during the pandemic. The City has since committed to a permanent year-round e-scooter program, and is in the process of selecting the vendors to provide and manage the scooters.

In this paper, we use simulation modeling to explore design issues and management strategies for a shared micromobility program based on e-scooters. Through analysis of the empirical 2019 and 2020 e-scooter data, we develop a detailed workload model including e-scooter trip characteristics, trip volume, and geospatial distribution within the downtown area. From this characterization, we construct a synthetic workload generator and a simulation model of Calgary's e-scooter system. We then use this simulator to conduct experiments that examine the performance of the e-scooter service as impacted by factors such as e-scooter fleet size, parking infrastructure location and capacity, and battery re-charging infrastructure. Our simulation results offer insights into promising management strategies for an e-scooter system.

The research contributions outlined in this paper are:

- a workload characterization of e-scooter trips in downtown Calgary based on empirical trip data;
- a discrete-event simulation model constructed from that characterization; and
- results from simulation experiments regarding fleet size, parking locations, and battery charging infrastructure.

The remainder of this paper is organized as follows. Section II provides background information on shared micromobility, and reviews prior related research on shared mobility and traffic simulation. Section III provides a workload characterization of e-scooter traffic. Section IV describes the construction and validation of our simulation model. Section V presents simulation results, including the scenarios considered and our findings. Finally, Section VI concludes the paper.

## II. Background and Related Work

This section provides some background information on the field of shared micromobility and transportation simulation.

### A. Shared Mobility

Shared mobility describes any transportation services that are shared by multiple users, including vehicle-sharing and ride-sharing services. The term 'shared micromobility' specifically encompasses bike- and scooter-sharing programs, such as those offered by companies like Bird, Lime, Roll, and Spin, who provide a fleet of vehicles for short-term rental use. These programs are rapidly gaining popularity around the world, with a reported market potential of $200-300B in the United States by 2030 [4]. At the time of writing, Lime has established shared mobility programs in more than 100 cities across the United States, Canada, and Europe [8], while Bird has more than 200 scooter-share programs worldwide [1].

There are many reasons why cities may want to pursue the development of shared micromobility services. Studies have shown that these programs create positive health impacts and reduce greenhouse gas emissions [14]. Moreover, increased availability of bike- and scooter-share options may also help to address transportation inequity by reducing reliance on individual vehicle ownership for transportation, and facilitating first-mile/last-mile connections to public transit [13].

In recent years, the focus of shared micromobility programs has begun to shift from bikes to scooters. In 2019, the National Association of City Transportation Officials reported that e-scooter usage had surpassed bike usage in shared-mobility trips, with 36.5 million bike-share trips and 38.5 million scooter-share trips in the United States the previous year [9].

In 2018, the City of Calgary announced a two-year pilot program on shared micromobility, with fleets of dockless bikes and e-scooters throughout the city. Anonymized trip data, amounting to approximately 450K trips, was collected in 2019 and made available to the public in 2020 [16].

### B. Related Work

The prevalence of e-scooters in shared mobility systems is a relatively recent development, so there are comparatively few studies on shared e-scooter programs. Nonetheless, the body of research on this topic has been growing rapidly with the increasing public interest in shared e-scooters. As shared micromobility continues to develop and become more established within transportation ecosystems, understanding traffic patterns, costs and benefits, and necessary infrastructure will be crucial in maximizing the efficacy of these systems.

Prior studies of shared e-scooters have focused primarily on characterization and behavioural analysis of the users. In 2017, Sheehan et al. [13] discussed the relationship between shared mobility and transportation equity, and identified specific geographic, economic, social, and technological barriers to access. In 2020, Jiao and Bai [6] examined 1.7 million e-scooter trips in Austin, TX between April 2018 and February 2019, and confirmed that e-scooter usage tends to correlate with specific elements of the built environment, such as university campuses or the downtown. Reck et al. [11] investigated the influences of factors such as distance and time of day on the choice that users make between different shared-mobility vendors and different modes of transportation.

Another common approach to studying disruptive transportation technologies is to use simulation or case studies to examine the impact of policy or technology on the efficacy of these systems, or to consider possible approaches to addressing known challenges. For example, Clemente et al. [2] identified the key challenges of the 'car sharing problem' as: (1) optimal fleet size; (2) location of parking areas; (3) pricing policies; and (4) flexibility of use. They investigated strategies for maintaining appropriate geographical distribution of vehicles without unduly compromising flexibility, via real-time monitoring and pricing incentives. Subsequently, Pfrommer et al. [10] examined similar issues with regard to public bicycle sharing schemes. They compared the effectiveness of a tailored routing algorithm for collection and redistribution of bicycles, and proposed dynamic incentives to encourage users to adjust the destinations of their trips. Our work is similar to these prior works, but with a specific focus on an e-scooter system.

More generally, simulation modelling has been used to evaluate public transport accessibility [5], and to determine optimal placement of EV charging stations to maximise the effective range of electric cars [12]. In 2016, Dia and Javanshour [3] conducted simulation experiments to assess the feasibility of using autonomous shared mobility vehicles. More recently, Yan et al. [17] used simulation modeling to determine optimal locations for battery-swapping stations to facilitate shared e-scooter travel between tourist destinations.

## III. Data and Analysis

We used two empirical datasets for the construction and validation of our simulation model, as described next.

The first dataset is the collection of detailed trip-level data from 2019, which is available [16] on the City of Calgary's open data portal. Table I shows the relevant headers from this dataset, which summarizes e-scooter trips on an hourly basis from May to December in 2019. Although these data include some geographic information, there is insufficient spatial resolution to derive any particular traffic patterns beyond an obvious concentration of scooter trips within the downtown area. For the purposes of our study, we filtered this dataset to focus solely on trips in the downtown area.

The second dataset consists of aggregate data from 2019 and 2020, including geographic information about scooter parking and scooter traffic volumes along individual streets. This dataset does not contain any trip-level information.

### A. Daily Traffic Volume

Figure 1 shows the total daily count of e-scooter trips in 2019 and 2020. The periodic spikes in the graph reflect weekly cycles, for which scooter usage differs between weekdays and weekends. The total daily trip volume is highest in the summer months (June to September), which is consistent with the weather conditions necessary for safe scooter operation.

TABLE I
OVERVIEW OF CITY OF CALGARY DATASET (2019)

| Field Name | Data Type |
|---|---|
| Start Date | Date |
| Start Hour | int (0-23) |
| Start Day | String |
| Trip Distance | int (meters) |
| Trip Duration | int (seconds) |
| Start Point | Point(Lat, Long) |
| End Point | Point(Lat, Long) |

The scooters were introduced to Calgary's streets later in 2019 (July) than in 2020 (May), resulting in different peaks in usage. The maximum fleet size also increased to 2,300 in 2020 from 1,500 in 2019. Despite the public health orders in response to the COVID-19 pandemic, which limited commuter traffic to and from the downtown, and reduced the permitted scooter fleet size in May and June, the overall trip volume is distinctly higher in 2020 compared to 2019. These trends suggest that demand for e-scooter shared mobility continues to grow.

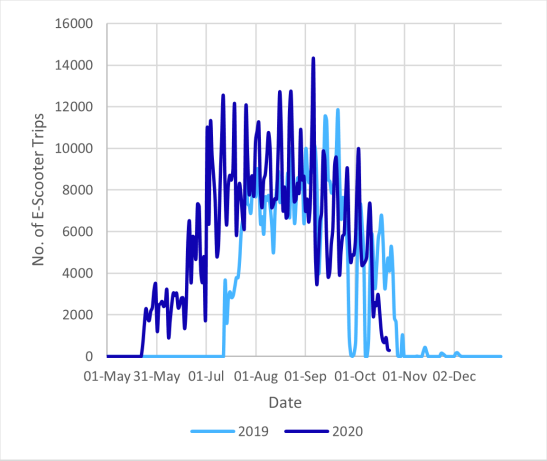



Fig. 1. Daily e-scooter trips in Calgary (2019 and 2020 data)

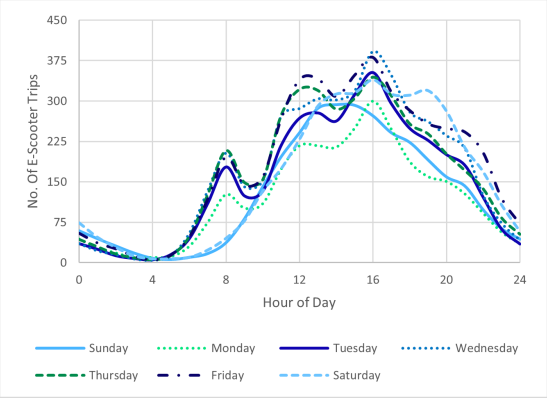



Fig. 2. Avg number of e-scooter trips by hour and day of week (2019 data)

### B. Hourly Trip Volume

An analysis of the average number of trips per hour reveals a clear diurnal pattern, as shown in Figure 2. Specifically, trip volumes peak around 4PM, and decline to their lowest values after midnight. Figure 2 also shows a notable difference between weekend and weekday traffic patterns. Weekday traffic follows a well-known tri-peaked behaviour [11], with distinct peaks at 8AM, 12PM, and 4PM, which correspond to morning rush hour, lunch hour, and evening rush hour, respectively. By contrast, weekend traffic increases later in the day, and has only a single peak in the early afternoon. All days have a slight 'shoulder' in the traffic patterns around 9PM, with this shoulder being most pronounced on Friday and Saturday evenings, and least evident on Sunday and Monday evenings.

### C. Geospatial Distribution

In both datasets, the majority of scooter trips originate from the downtown area. When broken down by neighborhood, the 2020 aggregate data shows that 68% of trips occur within the six neighborhoods at the heart of downtown.

Figure 3 is a heatmap showing the daily average trip count across each street in downtown Calgary. There is a high concentration of trips along the River Walk on the north (top) edge of downtown, with other noticeable concentrations along the $8^{th}$ Avenue pedestrian mall (adjacent to the downtown Light Rail Transit line), $12^{th}$ Avenue, and $17^{th}$ Avenue. There are also many scooter trips along $4^{th}$ Street and $5^{th}$ Street, which are two of the main connectors across the railway tracks separating the north and south parts of downtown.

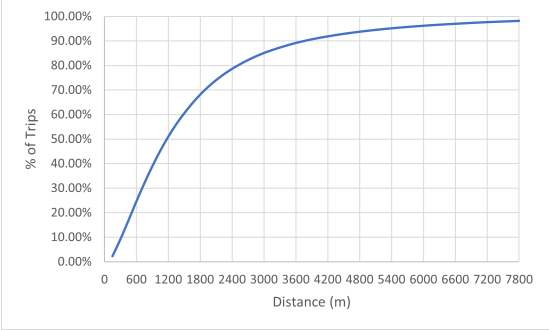

Fig. 3. Average daily trip volume on streets in downtown Calgary (2020 data)

### D. Trip Characteristics

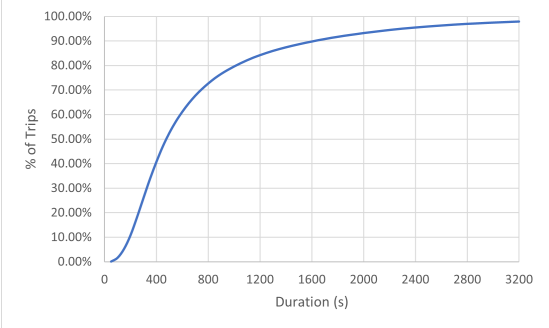
Figure 4 shows a statistical summary of the characteristics of e-scooter trips. From top to bottom, these graphs show the empirical distributions (histograms) for trip distance (in meters), trip duration (in seconds), and the average speed (in kilometers per hour, kph) during the e-scooter trip. The observed trip distances range from 100 m (i.e., slightly less than a typical city block) to more than 27 km. The mean trip distance is approximately 1.7 km. The shape of the distribution resembles an exponential distribution ($CoV = 1.04$), though the variance is higher, and the upper tail more pronounced.

Figure 5 shows that trip distance varies sharply by time of day. The predominant diurnal pattern shows a relatively steady

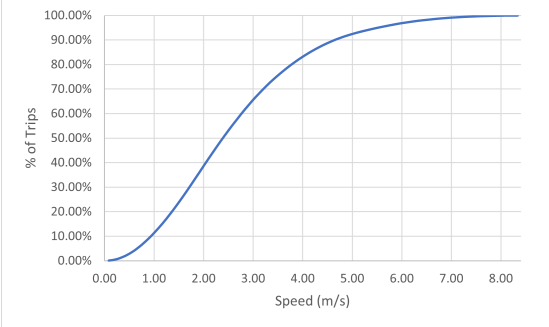
increase in average trip distance throughout the day, but with an abrupt drop in the wee hours of the morning. In addition, there is a pronounced difference between weekend trips and weekday trips. Weekends tend to have longer average trips with a peak earlier in the day, suggesting that these trips are recreational rather than for commuting.




(a) Trip distance (m)




(b) Trip duration (s)




(c) Average trip speed (kph)

Fig. 4. Empirical distributions for distance, duration, and speed (2019 data)

The trip durations follow a similar distribution to the trip distances, but deviate even more from an exponential distribution ($CoV = 1.08$). The shortest reported trip distance in the 2019 dataset is 30 seconds; the longest exceeds 2.5 hours.

The average trip speed, shown in Figure 4(c), does not resemble any immediately obvious distribution. These values are not reported in the 2019 dataset; rather, they are calculated (as a sanity check) from the distance and the duration. Interestingly, there is some correlation between speed and distance, as shown in Figure 6. While the maximum observed speed is near 30 kph (consistent with the reported top speed of many commercial e-scooters) regardless of trip distance, the

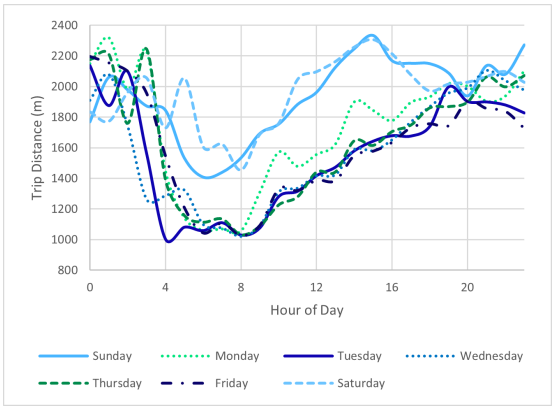



Fig. 5. Average trip distance (m) by hour and day of week (2019 data)

minimum observed speed increases steadily with trip distance. This makes sense intuitively, since people going on long trips are unlikely to do so slowly. Furthermore, users may grow more comfortable with higher speeds once they have become familiar with riding e-scooters.

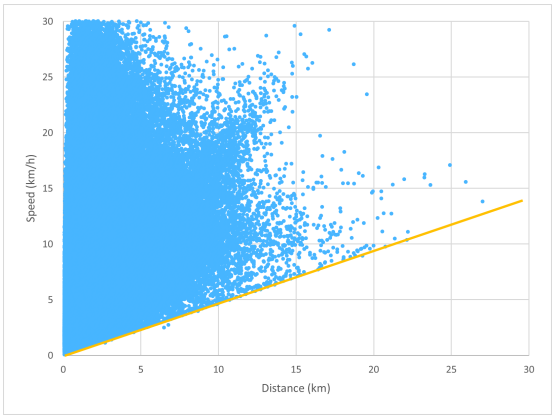



Fig. 6. Scatterplot of trip speed and trip distance (2019 data)

## IV. Simulation Model

Based on the empirical trip data, we developed a workload model to generate 30 days of synthetic e-scooter trips within a Java simulation environment. Table II shows the parameters and settings used. To reduce computational load while processing a month's worth of simulated trips on the geographic model of downtown Calgary, the simulation model focused on the events for: (1) beginning a trip; (2) ending a trip; and (3) the vendor collecting idle low-battery scooters to be recharged.

Several simplifying assumptions were made while constructing the simulation model, as follows:

- new e-scooter trips occur according to a Poisson arrival process, whose rate varies with time and day of week;
- users select e-scooters at random without preference for location or battery charge level, as long as the e-scooter has sufficient charge to complete the planned trip;
- no trips are abbreviated by low e-scooter battery level;

TABLE II
SIMULATION MODEL PARAMETERS

| Parameter | Default Value/Distribution |
|---|---|
| Number of Scooters | 500 |
| Inter-Trip Time | Exponential(hour, dayOfWeek) |
| Trip Distance | Exponential(hour, weekday/weekend) |
| Trip Speed | Empirical |
| Low Charge Threshold | 25% |

- all e-scooter trips maintain a constant speed between initial acceleration and final deceleration, with no stops;
- after recharging, e-scooters are returned to the fleet at the same location where they were picked up for recharging.

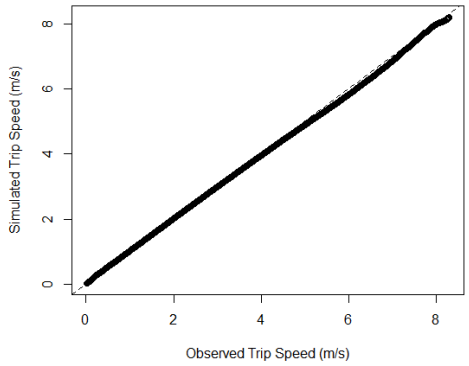
### A. Trip Generation

Because neither of our empirical datasets included trip start times at a sufficiently fine granularity to determine the empirical inter-arrival time distribution, we assumed that the arrival process would follow a Poisson (random) arrival process, though with time-varying rates. For this purpose, we constructed a 24x7 array to represent the mean inter-arrival time on an hourly basis for each day of the week. We then generate simulated inter-trip times at random from an appropriate exponential distribution. These inter-arrival times can be scaled by a constant factor to reflect the increased trip volumes reported in the 2020 aggregate data.

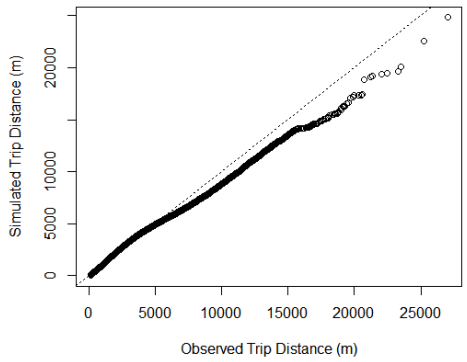
The target trip distance is similarly selected from an exponential distribution, using a 24x2 array of average hourly trip distances observed for weekdays or weekends. This distance determines the minimum bound for the average trip speed, which is then selected from the empirical distribution determined from the 2019 trip data.

As part of the validation for our synthetic workload model, we produced Quantile-Quantile (QQ) plots comparing the simulated trips with the empirical data from 2019. Figure 7 shows that the synthetic trip generation using these methods closely approximates real-world trips. The fit for trip speed is excellent (as expected, since the empirical distribution is used), while the fit for trip distance is satisfactory. The main deficiency is in the tail of the distribution, for which the exponential model is lighter than the empirical distribution.

When a new trip event is generated, a random e-scooter is selected from the pool of available e-scooters (i.e., not currently occupied, and not being recharged). If the e-scooter does not have sufficient battery level remaining to travel the full distance of the planned trip, a new e-scooter is randomly selected. If, after five attempts, no suitable e-scooter has been selected, the trip is counted as unfulfilled. Because both the 2019 and 2020 datasets contain information about *fulfilled* demand, it is difficult to determine ground truth for unfulfilled demand. Furthermore, since neither dataset provides sufficient detail about the directionality of traffic, we use the location of this randomly selected e-scooter to determine the origin point of the trip, rather than a randomly selected origin determining the e-scooter to be used.




(a) Comparing simulated and observed trip speed




(b) Comparing simulated and empirical trip distance

Fig. 7. QQ plots for validation of synthetic workload model

To generate a route for each trip, the simulation uses a deterministic algorithm that starts at the origin and iteratively extends the trip by selecting a neighbouring edge until the desired trip distance is achieved. Edge selection is weighted by the average daily trip count reported across that edge in the 2020 data. Backtracking is permitted only if no other edge choices are possible. Although this method does not directly model directionality of traffic, it should on average create a comparable spatial distribution of e-scooter traffic.

### B. E-Scooter Battery Model

We constructed a detailed model for e-scooter batteries based on the electric vehicle battery usage equations given by Kurczveil et al. [7]. Their formulae use kinematics to determine the energy transferred between the vehicle battery and the vehicle motor. In the following Equations (1)-(7), $v$ is the speed, and $\Delta s$ is the distance travelled. $E_{batt}$ refers to the chemical potential energy remaining in the battery, and $E_{veh}$ refers to the kinetic energy residing in the vehicle. We ignore potential energy since the downtown core in Calgary is relatively flat. $E_{gain}$ is the energy gained (or lost) by the battery between discrete time steps $k$ and $k+1$.

$$E_{batt}[k+1] = E_{batt}[k] + \Delta E_{gain}[k+1] \cdot \eta_{recup} \quad (1)$$

$$E_{batt}[k+1] = E_{batt}[k] + \Delta E_{gain}[k+1] \cdot \eta_{prop}^{-1} \quad (2)$$

$$\Delta E_{gain}[k] = E_{veh}[k] - E_{veh}[k+1] - E_{loss}[k] \quad (3)$$

$$E_{veh} = \frac{1}{2} m v^2 \quad (4)$$

$$E_{loss}[k] = \Delta E_{air}[k] + \Delta E_{roll}[k] \quad (5)$$

$$\Delta E_{air}[k] = \frac{1}{2} \rho_{air} \cdot A_{veh} \cdot c_w \cdot v^2[k] \cdot |\Delta s[k] \quad (6)$$

$$\Delta E_{roll}[k] = c_{roll} \cdot m \cdot g \cdot |\Delta s[k]| \quad (7)$$

Using these equations, battery usage is estimated based on distance travelled and the average speed. We use Equation (1) when the energy gain from the battery is positive (i.e., deceleration), and Equation (2) when the energy gain is negative (i.e., acceleration, or constant speed). Our simulation assumes each e-scooter battery contains 1350 kJ at full charge. Table III shows the other values used in our battery model.

To simulate e-scooter recharging, a recurring event is scheduled for 10PM each evening to represent the vendor managing their fleet. This event creates a list of every e-scooter with a depleted battery level below the charging threshold. We use a Shortest-Seek-Time-First algorithm to determine the order for scooter collection, starting from an arbitrarily chosen edge on the northeast corner of the simulation map. To reduce computational load, the distances are estimated using the Manhattan distance between latitude and longitude coordinates. The time required to collect the e-scooters is estimated from this distance using a constant truck driving speed of 30 kph, plus an additional 60 seconds for each edge where the vendor must stop to collect scooters, and an additional 30 seconds for each e-scooter to be loaded onto the collection vehicle. Scooter batteries are fully charged overnight, and the scooters are returned to the operational fleet the next morning.

TABLE III
PARAMETERS FOR MODELING E-SCOOTER BATTERY USAGE

| Symbol | Meaning | Value Used |
|---|---|---|
| $\eta_{prop}$ | Propulsion efficiency | 0.8 |
| $\eta_{recup}$ | Regenerative braking efficiency | 0.01 |
| $\rho_{air}$ | Air density | 1.225 |
| $A_{veh}$ | Drag area of scooter and rider | 0.875 $m^2$ |
| $c_w$ | Drag coefficient | 1.2 |
| $c_{roll}$ | Rolling resistance coefficient | 0.008 |
| $m$ | Mass of scooter and rider | 94 kg |
| $g$ | Acceleration due to gravity | 9.81 $m/s^2$ |

## V. SIMULATION RESULTS

This section presents the results from our three main simulation experiments, which consider the effects of fleet size, parking infrastructure, and battery recharging stations.

### A. Fleet Size

The first simulation experiment focuses on scalability aspects of the e-scooter system, by varying the number of e-scooters. The purpose is to gauge the impact of fleet size on relevant performance metrics, such as unfulfilled trips, improperly parked scooters, and the driving time/distance required to collect, recharge, and redistribute e-scooters.

Table IV shows the results of these experiments, which vary the e-scooter fleet size from 100 to 1600 (by factors of two). Unsurprisingly, smaller fleet sizes (e.g., 100 or 200 e-scooters) have more unfulfilled trips, and fewer e-scooters in use at a time. However, as the e-scooter fleet size increases, the average number of scooters concurrently in use reaches a plateau around 65 scooters. This result is a manifestation of Little's Law, a well-known conservation law from the field of queueing theory. For our baseline fleet size of 500 e-scooters, $\lambda = 0.0664 \frac{trips}{s}$ and duration $T = 981.6s$, so the average number of e-scooters in use at one time should be $N = 65$. When some trips are unfulfilled, the observed usage is lower.

The results in Table IV also show that as the fleet size increases, the time and driving distance required to collect scooters increases, and the percentage of trips ending at a designated parking zone decreases. These undesirable trends reflect an excess supply of e-scooters, resulting in many unused and/or improperly parked e-scooters. These concerns must be balanced against the desire to minimize the number of unfulfilled trips. Based on our simulation results, at the current demand level, the optimal number of e-scooters to operate within the downtown area is between 400 and 500.

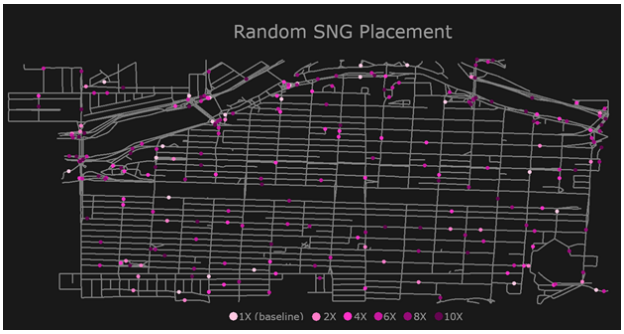
TABLE IV
EFFECTS OF E-SCOOTER FLEET SIZE

| Num. Scooters | 100 | 200 | 400 | 800 | 1600 |
|---|---|---|---|---|---|
| Max. in use | 100 | 182 | 208 | 199 | 195 |
| Avg. in use | 42.5 | 59.6 | 66 | 65.3 | 64.8 |
| Succ. trips/day | 3656 | 5227 | 5753 | 5750 | 5732 |
| Unsucc. trips/day | 2086 | 557 | 0 | 0 | 0 |
| % SNG-Parked | 2.87% | 2.99% | 2.97% | 2.95% | 2.90% |
| Avg. Coll. Time | 1:24:41 | 1:48:35 | 2:01:04 | 2:01:48 | 1:55:21 |
| Avg. Coll. Dist. | 24.5 km | 28.5 km | 30.7 km | 29.7 km | 27.9 km |

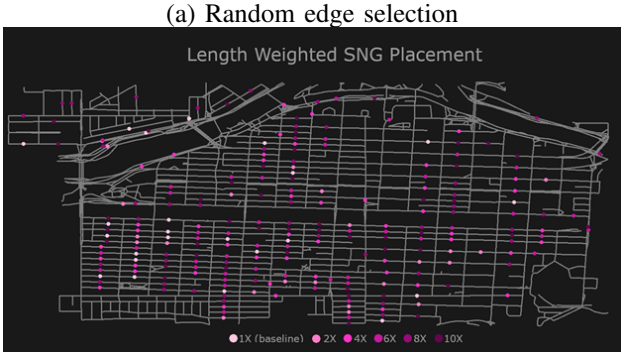
### B. Parking Areas

The second set of simulation experiments focuses on e-scooter parking. The aggregate data from 2020 included a JSON file of 23 Share-and-Go (SNG) parking zone locations within the downtown. We use these locations as the baseline in the simulation model, assuming sufficient space for 6 e-scooters at each SNG zone. We then determine the number of trips ending at a parking zone with available space.

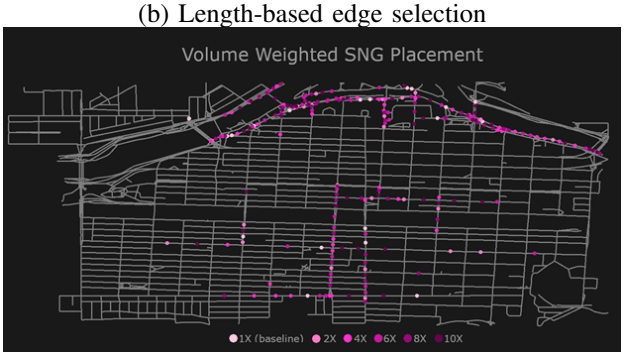
Our simulation experiments consider four strategies for placing additional scooter parking, increasing the baseline parking capacity by factors of 2, 4, 6, 8, and 10. The first strategy simply increases the size of existing SNG parking zones. The second strategy places additional SNG zone locations at random throughout the downtown area. The third strategy places additional SNG zones on the longest streets. The fourth strategy places additional SNG zones along streets with the highest e-scooter traffic volumes. Figure 8 provides a visual illustration of these latter three strategies.




(a) Random edge selection




(b) Length-based edge selection




(c) Volume-based edge selection

Fig. 8. Placement strategies for Share-N-Go (SNG) parking zones

In addition, these four sets of experiments were repeated with a modification to the simulation that allowed trips that ended on an edge with no available parking a 25% or 50% chance of extending to an adjacent edge with a parking space available. This variation tests the efficacy of nudging (e.g., discounts) to incentivize users to park their e-scooters properly.

Figure 9 presents the results from these simulation experiments. The vertical axis shows the percentage of e-scooter trips ending at an SNG zone with an available parking space (higher is better). The colored bars show the strategies.

The results in Figure 9 reveal three interesting trends. First, simply increasing the number of e-scooter parking spaces at the existing SNG zones is ineffective. Adding new parking zones is always better, even when the locations are selected at random. The improvements are magnified when SNG zones are placed according to edge length, and amplified further when assigned according to e-scooter traffic volume. These results suggest that the number and location of SNG parking

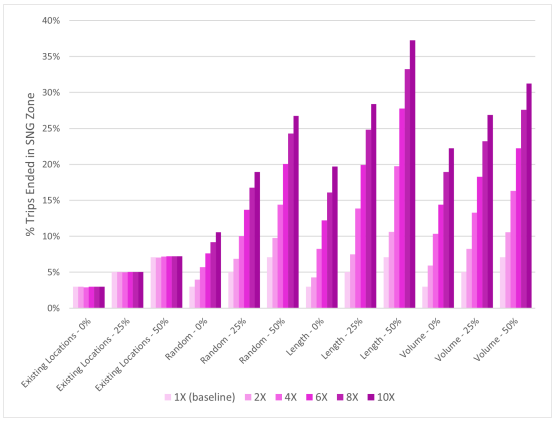



Fig. 9. Effects of expanding existing parking zones, and adding new zones at random, by edge length, and by volume, with 0%, 25%, and 50% chance of extending a trip to find parking on a neighbouring edge

zones is far more important than just the total number of parking spaces. Second, although the volume-based strategy for placing additional SNG zones yields the best results in terms of trips ended *at* an SNG zone, the length-based strategy is actually better when counting trips ending *at or adjacent to* an SNG zone. This is likely due to the proximal clustering of SNG zones induced by volume-weighted edge placement (see Figure 8c). Having greater geographic spread for the parking zones is better. Third, nudge strategies could be highly effective. That is, modifying the simulation to extend trips to adjacent edges with SNG zones resulted in significant improvement in all considered scenarios. However, achieving this behaviour in a real-world scooter system might require the implementation of incentives to improve proper parking.

### C. Battery Charging Stations

Our final simulation experiment is designed to assess the impact of installing e-scooter battery charging stations within the downtown area. Doing so could reduce the number of unfulfilled trips, as well as the driving time and distance required by vendors to manage their scooters.

Figure 10 shows the candidate charging locations considered in the simulations. Each of the 23 existing SNG zones (A-W, lighter) were considered, as well as ten additional locations (a-j, darker), chosen based on e-scooter traffic volume.


Fig. 10. Map of existing parking zones (A-W, blue) and high traffic edges (a-j, green) considered as candidate locations for charging stations

Three rounds of experiments were conducted, allowing for one, two, or three charging stations, each capable of charging up to six e-scooters at a time. After running an initial test with only one charging location, and comparing the number of scooters charged for the 33 candidate locations, the top ten locations (L, E, R, K, W, B, C, c, a, V) were selected for consideration in the next round. After running the second set of tests, with pairs of charging locations chosen from the contenders, the seven best-performing locations (R, W, B, C, c, a, V) were used in the final tests with three charging stations.

Figure 11 shows the results from these experiments. As expected, the percentage of trips ending at a charging station with an available charging bay (purple; higher is better) increases when there are more charging locations. However, there are diminishing returns: the first and second charging location each have a pronounced effect, while adding the third one has only a marginal benefit. Among the seven best locations identified, four (R, B, C, V) are along $17^{th}$ Avenue, and three (a, c, W) are along the River Walk. These locations make sense intuitively, since they are high-traffic areas for people, bikes, and scooters, especially on evenings and weekends.

Finally, Figure 11 shows the effects of the charging stations on collection time (pink line; lower is better) for the vendors when managing their fleet of scooters. From an average daily collection time of 2 hours with no charging stations, the average daily collection time decreases by 10% to 1 hour and 50 minutes for the best combination of three charging stations.

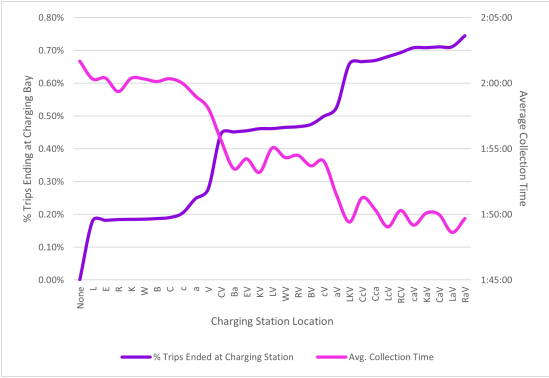



Fig. 11. Effects of charging stations on availability and collection time

## VI. Conclusions

In this paper, we have presented a workload characterization study and a simulation model of the e-scooter pilot project in downtown Calgary. Through experimentation with our simulation model, we have identified multiple important factors impacting e-scooter parking and collection costs.

The key findings of this paper may be summarized as follows. First, the appropriate number of e-scooters to be deployed in downtown Calgary is between 400 and 500 scooters. Second, increasing the number of parking zones for e-scooters is far more effective than simply increasing the number of spaces at existing parking zones, especially if users can be nudged to properly park their scooters. Third, installing one or more charging stations in the downtown area would help reduce operational costs for e-scooter vendors.

Future enhancements of our simulation model could include the implementation of e-scooter battery-swapping stations, or more refined models for trip origin/destination based on empirical data and knowledge of transit hubs.

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