High-Fidelity Modeling of Curbside Driving Behavior in SUMO

Preprint

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High-Fidelity Modeling of Curbside Driving Behavior in SUMO

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Abstract

1 Introduction

Recent advances in mobility technologies have significantly increased the demand for curbside use. At airports and in dense urban cities, the advent of Transportation Network Companies (TNCs), such as Uber and Lyft, led to an increase in curbside demand and congestion and a decline in the use of traditional travel modes, such as public transit and personal cars [1, 2]. In dense urban areas, curbside activities was further increased by the growing adoption of e-commerce and the demand for direct delivery of goods to their final destinations [3]. Capturing the complex maneuvering and interactions of vehicles at curb-lanes requires high-resolution vehicle microscopic modeling that is usually not inherently represented in traffic simulators [4]. In this paper, we present such a high-fidelity modeling of curbside driving behavior in the Simulation of Urban Mobility (SUMO) tool [5].

In literature, SUMO has been popularly used to model and evaluate on-street curbside parking [6, 7, 8]. However existing works do not focused on high-fidelity representation of the maneuvering and interactions of vehicles at curb-lanes as vehicle complete pick-up or drop-off trips. For example, reference [8] includes two main actions in their SUMO curbside parking simulation: a "parking-in-order" action, which requires vehicles to prioritize parking in slots closest to the upstream of the a parking lane, and an action that allows multiple vehicles to overtake a stopped vehicle. The authors of [9] uses SUMO to model how people get dropped-off or picked-up by shared fleets of fully automated vehicles at curbs near rail-stations, but without detailed modeling of the vehicle interactions at those curbs. [4] uses SUMO to evaluate optimal decisions of space allocation at curbs, including on-street parking, TNCs pick-up/drop-off, bus stops and through traffic, but without high-fidelity representation of vehicle curbside driving interplay.

Additional curbside maneuvering behaviors not considered in the above works include: more dynamic vehicle pick-up/drop-off (PUDO) locations compared to default SUMO PUDO locations, vehicles looking for free slots for pick-up or drop-off, and vehicles saving time by completing pick-up/drop-off in the lanes next to the curbside during highly congested time (also know as *double-parking*). These complex curbside driving behaviors are observed the most at airport terminal curbs, where vehicles have limited time to pick-up/drop-off passengers due to time-constraints on flight schedules or limited terminal curb space. SUMO built-in driving models do not innately represent such high-resolutions curbside behavior, but only queue vecicles one after another on curb lanes. To represent these complicated curbside driving behavior, we developed a customized curbside driving behavior model using the SUMO interface, TraCI, as follows:

- Acquire a list of all the vehicles on the curbside edges for vehicle behavior control;
- Use lane area detectors [10] to sense the availability of the curbside;
- Assign a stop to a newly arrived vehicles at the curbside;
- Assign a new stop to the vehicle if the vehicle is stopped and its destination stop is occupied by another vehicle.

2 Methodology

We modeled the curbside driving behavior by setting vehicles' stops at different locations in SUMO through TraCI. Figure 1 illustrates the flowchart of a vehicle's curbside behavior. At each step, we first acquired the list of all the vehicles located at the curbside edges. Each vehicle will be controlled following the flowchart in Figure 1.

We first check if the vehicle is on its PUDO destination edge, as there may be multiple edges being used as PUDO edges in the network. A vehicle could be on a curbside edge but just passing that edge.

For a newly entered vehicle at its destination PUDO edge, it will be randomly assigned to an open curbside space. In the simulation, the vehicles were generated with a designated curb stop at its PUDO destination edge. That stop will be removed once a vehicle entered the PUDO destination edge and a new stop will be assigned based on the curbside space availability. The curbside spaces are discretized into multiple parking spots. The parking spots are located on the right most lane of the edge. We used lane area detectors to sense if a parking spot is occupied (the blue rectangles in Figure 2). The spot without

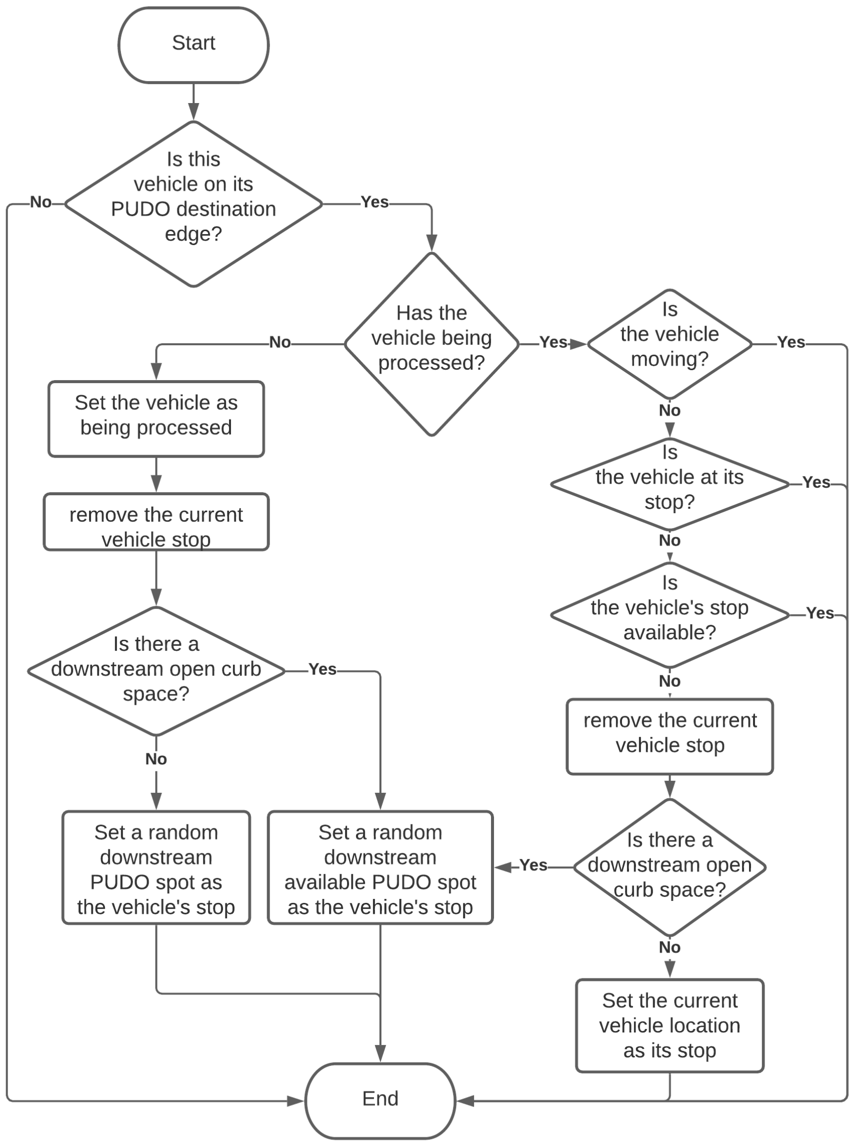

Figure 1: Curbside behavior flow chart

a vehicle on top of the detector was available. We treated the parking spot as available if the vehicle on the parking spot is accelerating or at a high speed, i.e., the vehicle is leaving that spot. If all the parking spots are occupied, the vehicle will randomly set a parking spot as its next stop. The vehicle will move towards that stop and will slow down to stop and wait for that stop to become available.

In reality, people will keep looking for downstream open curbside space as they drive if they cannot find a spot around them and also could double-park (i.e., stop at the second lane beside the curbside lane to do pick-up/drop off). Therefore, the algorithm keeps monitoring the processed vehicles (i.e., the vehicles with newly assigned stops at the curbside). If a vehicle is stopped because of a leading vehicle blocking its way (i.e., speed is zero but its status is not stopped at its assigned stop), it will find a new stop. The new stop could be at the curbside or at vehicle's current stopped location. If there is a downstream open curb space, the vehicle will randomly select an available PUDO spot as the new stop. If the downstream curbside space is fully occupied and serving other vehicles, that vehicle will set the current location as its new stop. Since the vehicle was already stopped, we made use of that waiting time to pick up or drop off passengers. This is to model the double parking behavior at the curbside.

3 Results

For our analysis, we looked at how our curbside maneuvering differs from the default settings in SUMO. Additionally, we analyzed the simulations from a congestion and capacity viewpoint. To ensured network integrity, we set the speed limits on the PUDO curbs by the observed ground truth speed we saw during free-flow conditions from real-world PUDO zones. The network for all simulations was set to 3 lanes, with 2 incoming lanes and 2 outgoing lanes (see Figure 2). Next, we built out a range of demand not to exceed the capacity of the two incoming lanes. Combining the demands and networks, we added the above described behavior which increased the capacity of the road. This in turn affects network saturation resulting in congestion that may occur suddenly and with inappropriate timing.

Figure 2: Base Network configuration with 10 curbside spots

The congestion observed from the SUMO's default curbside behavior is typically caused by vehicles stopping in the first available spot following the lead vehicle. This behavior seen in Figure 3, on the left, shows two gaps available, yet the vehicles remain in a platoon waiting to approach the curbside. This behavior is inefficient and unlikely to occur in reality. Considering this network configuration, we would more likely see vehicles maneuver around the queue of vehicles to look for open spots and proceed to fill in the gaps. On the right side of Figure 3, we see vehicles stopped in the middle lane waiting to change over to the curbside lane. The time waiting for an opening is wasted in simulation since the vehicle has to wait to change lanes to the curb-lane to complete their pick up or drop off. This in turn causes early congestion, as these vehicles have to stop and also hold up other vehicles behind them. Typically when this occurs at airports, the middle lane acts as a double-parking PUDO zone for vehicles. Thus, we would see these vehicles stop for a shorter dwell time in the second right-most lane to satisfy their pick up or drop off and then proceed on down the road.

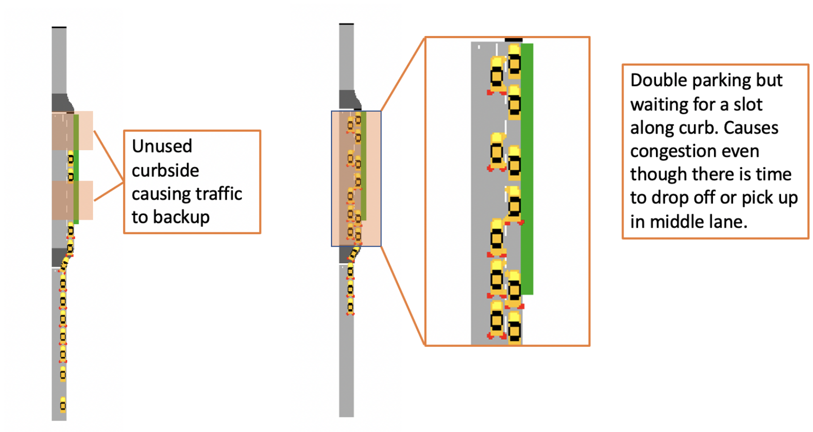

Figure 3: Displaying default behavior along curbside for PUDO

For this analysis, we ran tens of thousands of simulations to understand the effects of demand (incoming vehicles to the curb) on the simulation for various scenarios. We ran numerous demand levels along with various network configurations to produce charts showing how default PUDO behavior differs from our improved model. The network configurations were comprised of changing the number of curbside spots, where a curbside spot represents enough space for a typical passenger vehicle to park corresponding to 10 meters. We built networks with length ranging from 10 curbside spots up to 80. We also added buffer areas before and after the PUDO zones that were 10 meters each for gradual vehicle lane changing. The base configuration with 10 spots is in shown in Figure 2. Notice in Figure 2, we only count the spots along the curb. This is because these are the only valid spots for picking up or dropping off. The inside lane spots are only for high demand times when people begin to double-park. In total, the curbs went from 120 meters to 820 meters in length, for all simulated scenarios. The four metrics calculated here are: edge density, occupancy, waiting time and observed flow. Edge density is measured as number of vehicles per kilometer. Edge occupancy is the percentage of vehicles occupying the edge. 100 percent occupancy is the max value and can only occur if we set the minimum gap between vehicles to zero. We have our minimum gap set to 2.5 meters. Waiting time is the total number of seconds vehicles were considered halting below a speed threshold aggregated over the edge. Last, the observed flow is the actual flow measured during simulation in vehicles per hour (vph). For the following figures, the solid blue line represents the aggregated average metric for the improved curbside behavior. The grey dashed line represents the aggregated average metric of the default settings in SUMO. All aggregations were done over the full range of curb spots (10-80) and 3 lanes. They were displayed using various input demands (i.e., 100-3500 vph) and as many as 75 random seeds for each configuration of the simulation. The transparent shaded areas show the distribution from minimum values to maximum values of the metric being displayed.

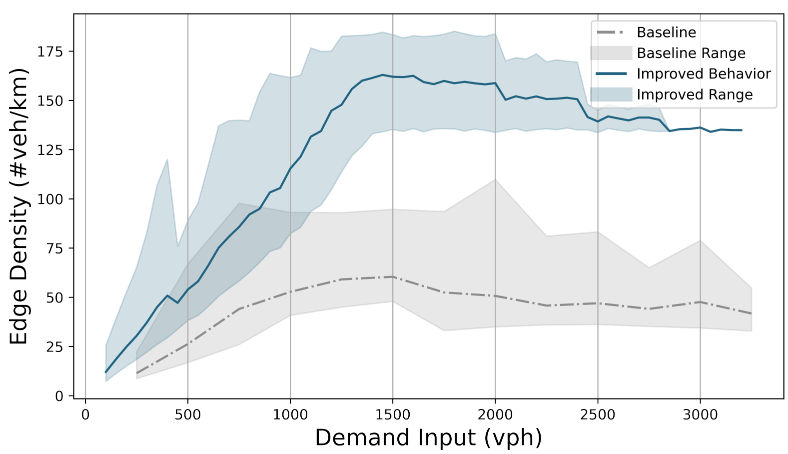

Figure 4: Comparing density between default behavior in SUMO with improved curbside behavior aggregated from various configurations (i.e., 10 curb spots to 80 curb spots)

In Figures 4 and 5, we notice that the input demand increases the density and occupancy for both models till it plateaus around 1500 vehicles per hour. However, the improved model has significantly greater average density/occupancy. These charts show that the capacity increases using the improved model. This is partly due to a more reasonable way of assigning vehicles to the curbside, but it also is happening due to the double-parking we programmed for higher demand scenarios. This double-parking behavior has been observed in real world airports during high demand hours.

Even more interesting, we observe that in Figure 6 waiting time seems to be very similar amongst all the input demand. The waiting time is less for the improved model up to 1500 vph input demand and then stays relatively close to

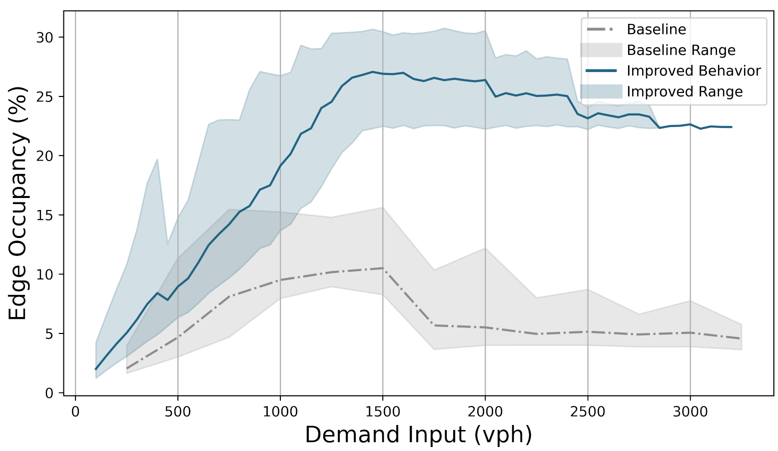

Figure 5: Comparing occupancy between default behavior in SUMO with improved curbside behavior aggregated from various configurations (i.e., 10 curb spots to 80 curb spots)

the default model after 1500 vph. This indicates that congestion level is similar in both scenarios, but the capacity is higher in the improved model, resulting in greater flows for the improved PUDO model. Thus, this model can be used to tune the capacity more appropriately with ground truth data since the capacity of the network can be derived from the observed data. Additionally, we can see the distribution range of the improved model is more narrow than the default, showing the model is more stable given various scenarios.

In Figure 7, notice the observed volume of the improved PUDO model is greater for all input demands. Also, the volume ranges are tighter for the improved model. Combining all these metrics, we can see the improved PUDO model increases the capacity of the curbside while keeping the congestion (waiting time) relatively similar. The improved behavior is built on driving movements observed at an airport. More importantly, this model can be tuned and adjusted to increase or decrease the capacity of the simulation for curbside PUDO simulations for enhanced models.

4 Conclusion

The recent emergence of TNCs and increased use of e-commerce have significantly augmented the need for curb space and curbside congestion. This has created a need for high-resolution and accurate modeling of vehicle curbside behavior, which is not inherently modeled in microscopic simulators such as SUMO. In this work, we presented a high-fidelity simulation of curbside vehicles' maneuvering and interactions in SUMO. The improved curbside behavior

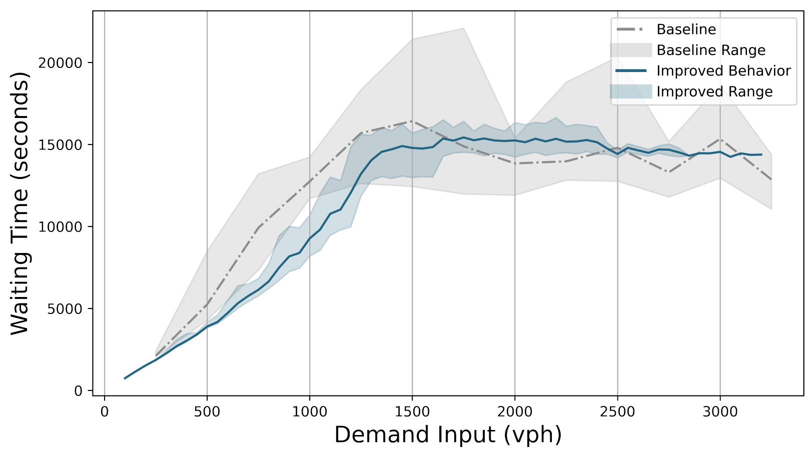

Figure 6: Comparing waiting time between behavior in SUMO with improved curbside behavior aggregated from various configurations (i.e., 10 curb spots to 80 curb spots)

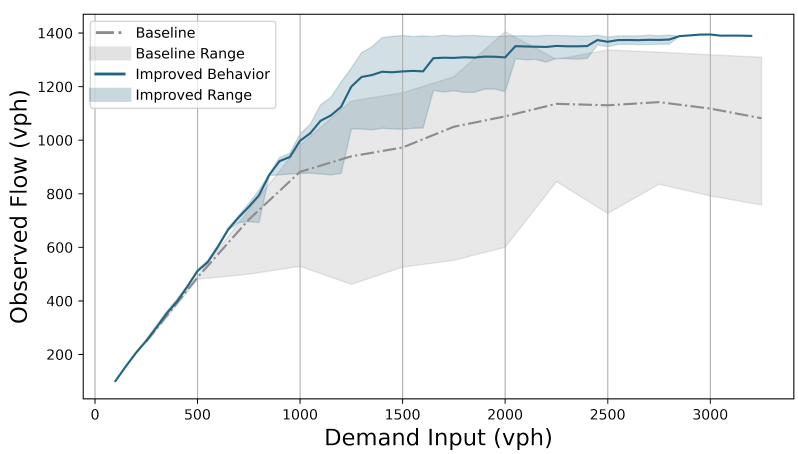

Figure 7: Comparing observed flow between default behavior in SUMO with improved curbside behavior aggregated from various configurations (i.e., 10 curb spots to 80 curb spots)

incorporates more realistic interplay of vehicles at the curb compared to the built-in SUMO curb behavior. These include randomized PUDO location, vehicles looking for free slots for pick-up or drop-off, and vehicles saving time by double-parking in the lanes next to the curbside during highly congested time. These behaviors were modeled in SUMO using the TraCI interface. Simulation results, that compared the improved curbside behavior versus the default SUMO curb queuing behavior, showed that the improved curbside behavior exhibited more realistic vehicle actions and increased the curbside capacity and utilization while maintaining the same vehicle delay times.

References

[1] P. Mandle, S. Box, Transportation network companies: Challenges and opportunities for airport operators, no. Project A11-03, Topic S03-11, 2017.

[2] M. Diao, H. Kong, J. Zhao, Impacts of transportation network companies on urban mobility, Nature Sustainability (2021) 1–7.

[3] Q. Chen, A. Conway, J. Cheng, Parking for residential delivery in new york city: Regulations and behavior, Transport Policy 54 (2017) 53–60.

[4] S. Young, A. Henao, Cities topology-curbs and parking, Tech. rep., National Renewable Energy Lab.(NREL), Golden, CO (United States) (2020).

[5] M. Behrisch, L. Bieker, J. Erdmann, D. Krajzewicz, Sumo–simulation of urban mobility: an overview, in: Proceedings of SIMUL 2011, The Third International Conference on Advances in System Simulation, ThinkMind, 2011.

[6] A. Hakeem, N. Gehani, X. Ding, R. Curtmola, C. Borcea, On-the-fly curbside parking assignment., MobiCASE 16 (2016) 1–10.

[7] J. Arellano-Verdejo, E. Alba, Optimal allocation of public parking slots using evolutionary algorithms, in: 2016 International Conference on Intelligent Networking and Collaborative Systems (INCoS), IEEE, 2016, pp. 222–228.

[8] Q. Ye, S. M. Stebbins, Y. Feng, E. Candela, M. Stettler, P. Angeloudis, Intelligent management of on-street parking provision for the autonomous vehicles era, in: 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), IEEE, 2020, pp. 1–7.

[9] Y. Huang, K. M. Kockelman, V. Garikapati, L. Zhu, S. Young, Use of shared automated vehicles for first-mile last-mile service: micro-simulation of rail-transit connections in austin, texas, Transportation research record 2675 (2) (2021) 135–149.

[10] Lanearea detectors (e2), `https://sumo.dlr.de/docs/Simulation/Output/Lanearea_Detectors_%28E2%29.html`, accessed:2021-05-17 (February 2021).