Insights into Equitable and Fair Congestion Pricing Strategies in a World of Shared Automated Vehicles

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Problem Statement

As an applicable measure in traffic demand management contemporarily, congestion pricing has gained increasing interest from the public as well as the transportation authorities. Under the charging mechanism, unreasonable travel demand is consequently restrained, and a preferable distribution of traffic is completed on a network, which leads to a mitigation of traffic congestion. The cordon-based congestion pricing scheme is widely adopted by encircling a certain district within which commuters are required for congestion toll (Foo, 2000; Santo, 2008; Cheng et al., 2016.).

Many charging schemes applied currently are flat-toll charges, ignoring the disparities between each traveler, which results in serious inequity for the general public. Consequently, previous studies have proposed several alternative toll charge schemes such as distance-based, time-based, congestion-based, patron-based and so on (Gu et al. 2018; Huang et al. 2021). Owing to the advance of technique such as global positioning system (GPS) and radio frequency identification (RFID), an integrated distance-based toll structure becomes practical which enhances the social equity since the congestion tolls are proportional to the distances travelled by commuters, reflecting the true utilities and costs.

However, in spite of those benefits of congestion pricing discussed above, opposition against congestion pricing among the general public remains strong, due to the possible loss of public welfare (Jaensirisak et al., 2005). Most studies, which focus on congestion pricing assume that the demand of travelers is elastic, associated with less desirable schemes (e.g., shift travel time or use different mode of travel). However, travelers who switch travel schemes are not considered in the congestion pricing policy. In fact, in many cases, the trip rates taken between each origin and destination, especially in the peak hours, can be regarded as fixed demand (e.g., regular commute to work). During these periods most of the trips cannot be easily foregone or shifted. Therefore, a generalized congestion pricing scheme in a multi-modal network is established to better describe this social issue.

In recent years, transportation network companies (TNCs) such as Uber and Lyft have brought about a significant transformation in urban mobility. By providing on-demand car services, these companies have decoupled car access from car ownership, bridging the gaps in mobility that arise when individuals lack their own vehicles. However, despite their high-tech appeal, ride-hailing services do not offer equal accessibility to all neighborhoods and travelers. Ge et al. (2016) conducted a study and found that minority TNC riders experience significantly longer wait times, on average. Additionally, studies have revealed instances of discrimination by drivers from both UberX and Lyft, who sometimes cancel rides based on the perceived race of the passenger.

Autonomous vehicles (AVs) have the potential to revolutionize transportation. The deployment of AVs is rapidly approaching, with companies like Google's Waymo already operating fully autonomous taxis in certain cities, and numerous other technology firms conducting pilot operations (The Waymo Team 2022). AVs offer significant promise in promoting social equity by improving mobility for minority groups, low-income individuals, the elderly, and those with medical conditions that limit their travel options. However, like any emerging technology, shared

AVs also have the potential to worsen existing social inequalities. Unfortunately, most AV modeling efforts overlook the potential distribution of impacts and fail to consider equity considerations.

To ensure that the path towards vehicle automation reduces transportation inequity and leads to a smarter and more sustainable transportation system, this study employs agent-based simulation to evaluate how different congestion pricing schemes in shared AV systems affect overall system performance (e.g., congestion and operations) as well as outcomes for specific sub-populations (e.g., travel costs for different groups).

Case Study Area

This paper focuses on assessing the transportation system and sub-population level impacts of different congestion pricing policies for shared AV services in Seattle. While the conclusions of this research are meant to be generalizable, we focus our study on Seattle, Washington because it's a diverse city with known inequalities among income, race, and other factors. Areas outside of the city limits of Seattle are not in the scope of this study.

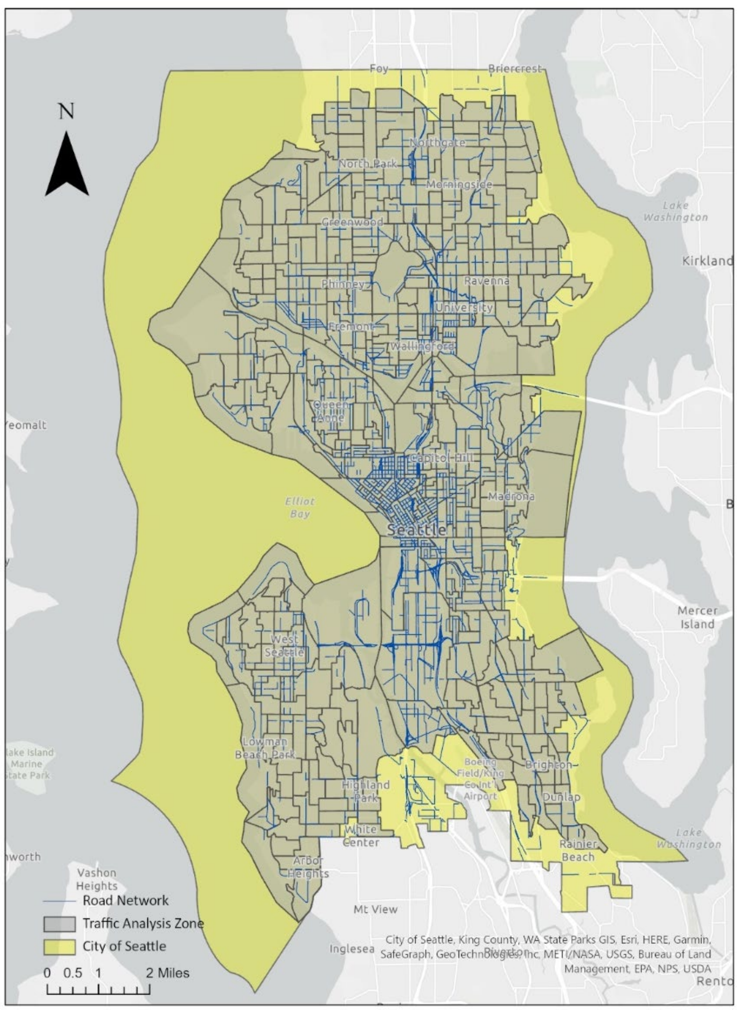

Figure 1. Study Region

Data

We extracted the road network data from OpenStreetMap and public transit network and schedules from General Transit Feed Specification (GTFS). Converting GTFS to transit schedules and mapping transit stops and transit routes to the road network are accomplished by pt2matsim tool. Transit modes (bus and tram in this study) will reflect congestion effects if they share the same road with private vehicles, otherwise dedicated artificial links are created and transit vehicles will travel in fixed schedule. After cleaning and simplifying the network, 27k nodes and 57k links are extracted as the multi-modal network.

Agent-based transportation simulation requires detailed information on the travel patterns of different travelers within the study region. A tour for each traveler is required in simulation preparation to represent the chain of trips each person takes throughout the day. In order to assign each traveler a set of trips we adopt the synthetic population from PSRC's (Puget Sound Regional Council 2014) DaySim model, which simulates and creates a daily activity and travel schedule for each person in the Puget Sound region in the year 2014. The synthetic population generated by SoundCast contains important demographic information for each traveler such as household income, person, age and gender and employment status. Each person in the synthetic population also has a daily travel schedule that details information such as origin and destination trip purpose, arrival and departure time, and mode used for each trip. The synthetic travel population from SoundCast are based on the 2014 PSRC Household Travel Survey, the American Community Survey (United States Census Bureau 2014), and other demographic related data sources (Puget Sound Regional Council 2014).

Overall, the synthetic population (home based in Seattle city) from SoundCast consists of about 625,000 people with 30% households being low-income (lower than $50k). In this study, we focus on several categories of subpopulation. The reference group is set as an employed adult (age 18-64) with car ownership and $100k - $150k household income. The elderly and/or low-income and/or unemployed groups are treated as vulnerable subpopulation and compared with reference groups.

Methodology

SAV configuration and MATSim simulation

We implemented SAV vehicles in the simulation as demand-responsive transportation (DRT) service by using MATSim's DRT module. These vehicles have a maximum capacity of 4 passengers, and the automation was reflected by the change of road capacity in a mixed traffic condition (In this case the SAV consists only 3% of the vehicles, which makes the capacity change ignorable). Ridesharing will be executed when ride requests are in the proximity of the vehicle and the agents have similar destinations, implemented in DVRP algorithm (Maciejewski et al. 2017). The SAV vehicles are randomly distributed across the simulation area. Idle vehicles will return to one of these starting locations as they are regarded as depots and all vehicles returned to their predefined, random locations after each day operation. The maximum waiting time is set to 20 minutes. the request will be rejected if waiting time exceeds the limit, although travelers have the ability to replan their activity by mutate departure time, mode choice, etc.

The cost of an SAV trip is calculated by distance-based pricing policy, which contains a \$2 fixed fare and distance-based fare of \$0.25 or \$1 per mile, which is the similar settings to (Liu et al. 2017). The operations cost function is calculated as follows, with operating parameters adopted from (Hörl et al. 2021) and are illustrated in parameter sections.

$$C_{fleet} = C_{perDistance} \times d_{fleetDistance} + C_{perTrip} \times n_{number\ of\ Trips} + C_{perVehicle} \times n_{number\ of\ Vehicle}$$

Choice dimensions and scoring function

In our simulations, the mode options include car, transit, bike, walk and SAV. Daily itineraries or agents' plans contain up to five different activity types: "home", "work", "shop", "school" and "others", which can be linked via several possible trip-chain combinations.

Regarding the mode split procedure, note that user equilibrium is not reasonable enough to depict the mode choice of traveler and goes far from the observed results. This process is influenced by a large number of factors, many of which are difficult to quantify and measure. To account for these factors in practice, the multinomial logit (MNL) model is applied as follows,

$$\Pr(m) = \frac{\exp(\theta S_m^w)}{\sum_{m \in M} \exp(\theta S_m^w)}, w \in W$$

where for each OD pair $w \in W$, $\Pr(m)$ is the probability of choosing mode m and θ is nonnegative empirical parameters associated with the degree of passenger's perception of travel cost and set to 1 in our model. S_m^w represents the scores (utility) of users choosing mode m between OD pair w.

In MATSim, the travel plan may be modified given constraints of one day time and real-time road conditions. Part of travelers will change their daily activities based on the utilities of individuals. Besides monetary costs and travel time, early departure, late arrival, or cancelling an activity will also affect activity utility. Agents' daily activities are modeled in MATSim through an iterative learning mechanism based on a quantitative score illustrated in the section below. The score of a plan is similar to the mode utility in the mode choice model but incorporates the additional utility (score) of activities (Axhausen and ETH Zürich 2016). The basic function of calculating the plan score is as follows,

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)}$$

where N is the number of activities in the plan, $S_{\mathrm{act,q}}$ refers to the score of activity q and $S_{\mathrm{trav,mode(q)}}$ represents the score of trips after activity q via $mode(q)$. The last activity is combined with the first one to have the same number of activities and trips. More specifically, the activity score is broken down as follows to capture the activity duration performance and late arrival penalty.

$$S_{act,q} = S_{dur,q} + S_{late\ arr,q}$$

$$S_{dur,q} = \beta_{dur} t_{typ,q} \ln\left(t_{dur,q}/t_{0,q}\right)$$

$$S_{late\ arr,q} = \begin{cases} \beta_{late\ arr}\left(t_{start,q} - t_{late\ arr,q}\right), \text{if } t_{start,q} > t_{late\ arr,q} \\ 0, \text{otherwise} \end{cases}$$

where $t_{\mathrm{typ,q}}$ (in hours) is the typical duration of activity q, $t_{\mathrm{dur,q}}$ is the actual duration of activity q, $t_{\mathrm{0,q}}$ is the duration when the utility of activity q starts to be positive. $t_{\mathrm{0,q}}$ is set to $t_{\mathrm{typ,q}}$exp ($-10/t_{\mathrm{typ,q}}$), $t_{\mathrm{start,q}}$ is the actual start time of activity q, $t_{\mathrm{latest\ arr,q}}$ is the latest start time of activity q without penalty. Without further information regarding travelers' preference for early departure/late arrival, we set these activity scoring parameters as default in MATSim.

Congestion Pricing Schemes

For this distance-based toll, the amount agents have to pay for the toll is linear to the distance they travel in the tolled area. The tolled area is selected as the downtown area where most congestion occurred.

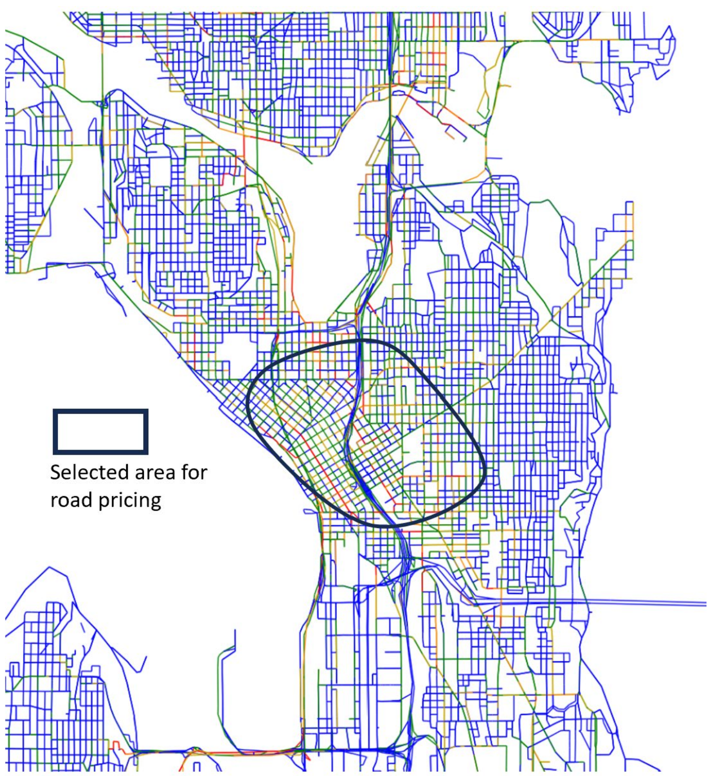

Figure 2. Toll Area for Congestion Pricing

Two tolling schemes are simulated under different SAV fleet size and pricing strategies. The two tolling schemes we investigated, are as follows:

- Scheme 1: From 7AM-9AM, 5PM-7PM, toll is $0.5 per mile in the cordon. From 9AM-5PM, toll is $0.1 per mile in the cordon.
- Scheme 2: From 5PM-7PM, toll is $0.5 per mile in the cordon.

Results and Recommendations

Road pricing will charge car users when they traverse specific links in the downtown area. All congestion-pricing scenarios evaluated here succeed in reducing the number of car trips. Overall, trips made by SAV and personally owned vehicles experience a slight increase in mode share, due to congestion pricing that makes car use more expensive. As shown in Table 1, when SAV fleet size is small, more car users switch to transit and walk. When SAV fleet size is oversupply (at a fleet size of 8000), SAVs will have higher mode share change compared to other mode because the shorter SAV wait times and less detoured distance from higher fleet size leads to SAVs being a more attractive mode for travelers.

Both toll schemes have similar effects on mode share, which pushes private car users to other modes. This can be explained by the fact that agents will evaluate their entire trip plans per day to decide their mode choice. For instance, in a home-based trip chain, due to subtour mode constraints, car drivers need to return their car back home if they decided to commute with private car.

Table 1. Mode Share Change Compared with Non-toll Scenario

SAV Setting	Toll Strategy	Bike	Car	SAV	Transit	Walk
SAV Fleet Size =1000, $1/mile	Toll Scheme 1	+0.1%	-2.5%	+0.7%	+0.8%	+0.9%
	Toll Scheme 2	+0.1%	-2.5%	+0.4%	+1.9%	+0.1%
SAV Fleet Size =5000, $1/mile	Toll Scheme 1	+0.4%	-3.1%	+0.7%	+0.8%	+1.2%
	Toll Scheme 2	+0.4%	-3.1%	+1.0%	+0.5%	+1.2%
SAV Fleet Size =8000, $1/mile	Toll Scheme 1	+1.5%	-3.4%	+1.7%	+0.4%	-0.2%
	Toll Scheme 2	0%	-1.6%	+1.4%	+0.6%	-0.4%

The VMT change in Table 2 shows a similar pattern with mode share change, that is less car VMT, but more SAV VMT is created. With a heavier tolling scheme (scheme 1), there's a slightly more decrease in total private car travel distance and higher SAV travel distances.

Table 2. VMT Change Compared with Non-toll Scenario

SAV Setting	Toll Strategy	Car	SAV
SAV Fleet Size =1000, $1/mile	Toll Scheme 1	-0.19%	+0.55%
	Toll Scheme 2	-0.17%	+0.17%
SAV Fleet Size =5000, $1/mile	Toll Scheme 1	-0.35%	+0.36%
	Toll Scheme 2	-0.32%	+0.25%
SAV Fleet Size =8000, $1/mile	Toll Scheme 1	-0.95%	+0.40%
	Toll Scheme 2	-0.85%	+0.13%

To evaluate the social equity of congestion pricing effects among subpopulations, the synthetic population is split into two subpopulation groups based on several different socioeconomic characteristics (i.e., household income, employment status, and age). These factors were selected because they play a role in transportation mode choice decision-making and understanding their heterogeneous effects on mode choice is an important precursor to assess the effects of congestion pricing on mobility and equity. The reference group is set as employed adults (age 18-64) who have a household income above $100k, which belongs to middle to upper class given the median salary of 81k in Seattle in 2014. People who are elderly, low-income, and/or unemployed are considered disadvantaged subpopulations and compared with the reference group.

Table 3 shows the utility changes comparing these two subpopulation groups. Overall congestion pricing has a negative effect on travelers' utility, mainly because higher monetary costs are generated for trips. The disadvantaged group has a higher utility decrease compared to their wealthier counterparts. This is mainly because disadvantaged groups are mostly from low-income households and are more sensitive to external costs. In some scenarios (e.g., with 8000 fleet SAV), the reference group experiences an overall utility increase. This can be explained by less congestion during peak hours and the benefits of using SAV where the reference group could gain more travel time savings with driverless vehicles. The results indicate an inequity issue inherently occurred in congestion pricing applications, due to the fact that different subpopulations have various attitudes towards external costs and travel time savings.

Table 3. Utility Change in Subpopulations

SAV Setting	Toll Strategy	Disadvantaged group	Reference group
SAV Fleet Size =1000, $1/mile	Toll Scheme 1	-12.6%	+1.0%
	Toll Scheme 2	-6.9%	-3.6%
SAV Fleet Size =5000, $1/mile	Toll Scheme 1	-15.6%	-6.3%
	Toll Scheme 2	-16.5%	-8.2%
SAV Fleet Size =8000, $1/mile	Toll Scheme 1	-14.1%	+4.1%
	Toll Scheme 2	-6.0%	+2.1%

Table 4 summarizes the collected toll information. In toll scheme 1, with SAV fleet size increases, the total collected toll increases, because more mode switch to SAV and SAV operators were also charged for the toll. Since congestion pricing pushes more private car users to other modes, the number of people who paid toll is decreasing with SAV fleet size increases. The average paid trip length decreases with fleet size increases, which means people tend to avoid longer distance trips by car in the tolled area, and the increase of SAV fleet size attracts shorter trips. Toll scheme 2 shows a similar trend to scheme 1, and with the only charges from evening peak hours compared to the entire daytime in scheme 1, it collects about 35% of the total amount of toll.

Table 4. Collected Toll Summary (in 5% scale)

SAV Setting	Toll Strategy	Number of people who paid toll	Total toll amount ($)	Average paid trip length (meter)
SAV Fleet Size =1000, $1/mile	Toll Scheme 1	13,087	8,432	651
	Toll Scheme 2	3,854	3,018	282
SAV Fleet Size =5000, $1/mile	Toll Scheme 1	11,826	8,549	424
	Toll Scheme 2	3,538	3,056	130
	Toll Scheme 1	11,113	8,566	351

SAV Fleet Size =8000, $1/mile	Toll Scheme 2	3,305	3,063	98

Conclusion and Future Work

This study uses agent-based simulations to evaluate distance-based congestion pricing in selected areas of the city of Seattle, WA. Different SAV settings are also tested with the proposed congestion pricing schemes. Results show that congestion pricing influences people's decisions of mode choice and travel utilities. Since road use is more expensive, congestion pricing pushes some people from private car to public transit and more active transportation modes. The toll scheme which only charges a toll during evening peak hours (Scheme 2) has a similar effect compared to the toll scheme which charges at different time periods during the day (Scheme 1). Different SAV fleet sizes also change the effects of congestion pricing. People tend to switch to SAV and use SAV for shorter trips if the fleet is over-supply. By comparing the utility changes of disadvantaged group and reference groups, we conclude there's inequity issue occurred in a simple distance-based pricing schemes, because people with different value of time/household income would react differently to the external costs.

Although this study provides some insights into how congestion pricing with SAVs affects mode share and traveler utility, there are opportunities for future work. First, in future simulations, we should evaluate the scenarios where SAV users will be responsible for the congestion toll, which will likely further decrease the mode share of SAVs. Second, more complicated congestion pricing schemes will be tested, which depends on the dynamic road congestion conditions, to better serve the purpose of congestion pricing to eliminate unnecessary car trips and promote a more equitable transportation system.

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