COMPARING CONGESTION PRICING STRATEGIES WITH EVIDENCE FROM A LARGE-SCALE SIMULATION FRAMEWORK

Kentaro Mori
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
mori@utexas.edu

Felipe de Souza, Ph.D.
Transportation and Power Systems Division
Argonne National Laboratory
9700 S. Cass Avenue
Lemont, IL 60439
fdesouza@anl.gov

Krishna Murthy Gurumurthy, Ph.D.
Transportation and Power Systems Division
Argonne National Laboratory
9700 S. Cass Avenue
Lemont, IL 60439
kgurumurthy@anl.gov

Joshua Auld, Ph.D.
Transportation and Power Systems Division
Argonne National Laboratory
9700 S. Cass Avenue
Lemont, IL 60439
jauld@anl.gov

Kara M. Kockelman, Ph.D., P.E. (corresponding author)
Dewitt Greer Centennial Professor in Engineering
Department of Civil, Architectural, and Environmental Engineering
The University of Texas at Austin
kkockelm@mail.utexas.edu
Tel: 512-471-0210

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ABSTRACT

Assessing congestion pricing policies prior to implementation requires careful consideration of behavioral responses across multiple choice dimensions and heterogeneity among travelers, aspects often overlooked in previous studies. This study compares the impacts of cordon, distance-based, and delay-based tolling strategies for the case of Austin, Texas, using the POLARIS agent-based activity-based travel demand simulation model. To ensure comparability, distance-based tolls were set to generate the same revenue as delay-based tolling of $4.06 M per day, averaging $1.37/person per day or $0.51 per vehicle-trip. Results indicate improvements in network efficiency under delay-based tolling, but reductions in delay hours under distance-based pricing seem to primary stem from reductions in the distances driven. A cordon toll of $4.83 per entry into the core Austin area, generating revenue proportional in terms of trips affected to the other two strategies, had negligible impacts on the network. Interestingly, the delay-based pricing strategy elicited travelers to shift towards the PM peak instead of having a peak-shaving effect. The spatial distribution of toll burden by residential location revealed disproportionate impacts of tolling in the delay- and distance-based tolling strategies. Residents of central Austin incur the highest tolls under delay-based pricing, while those in outer areas pay the most under distance-based pricing. These results and modeling practices can inform planners and policymakers worldwide who are looking to congestion pricing as a solution to meet the mobility needs of increasing urban populations while reducing congestion.

Keywords: *Road pricing, congestion pricing, equity, agent-based modeling.*

BACKGROUND

Congestion has been a decisive measure used to understand regional travel productivity by local planning agencies for the past several decades. Road infrastructure projects are approved or rejected by DOTs and transportation departments using metrics such as vehicle-miles traveled (VMT) or vehicle-hours traveled (VHT). Since the Great Recession, travel demand is on an increasing trend and far outpaced infrastructure investments (Polzin and Chu, 2014). Data from the USDOT suggests that most of this travel in the United States is made in single-occupied vehicles (Bureau of Transportation Statistics, 2024). The year-over-year increase in car travel, when accompanied with a decrease in transit ridership, has resulted in severe congestion in most urban regions. In 2022, an average American driver lost 51 hours to congestion (Pishue, 2023).

Nearly all transportation professionals agree that building more infrastructure in major metros is not the solution to curb this congestion. Induced demand as a result can simply shift the bottlenecks or impose marginally lower delays on a wider segment, resulting in more time spent stuck not moving on a road. While infrastructure is the cornerstone of productivity, an excess of it does not guarantee multifold benefits and an adequate amount is sufficient for rural and urban areas alike. On the other hand, travel demand management strategies like charging for parking, providing high-occupancy lanes, levying road use tolls, promoting remote work, incentivizing commuter transit pass use, and vanpools among many others have been employed by agencies in the US for some time now. Such strategies have shown to lower auto travel demand considerably and ease regional congestion.

A bittersweet example on the extent of benefits in travel demand management is the COVID-19 pandemic. Although the pandemic left hundreds of millions battling the virus, overloading hospitals, it was a natural travel demand management intervention. Most of the workforce shifted to remote work, and schools eventually moved online. Trips made were overwhelmingly mandatory essential activities and those by healthcare professionals (Abdullah et al., 2020). This event eased congestion temporarily, lowering greenhouse gas (GHG) emissions and travel-related noise, and a general increase in air quality (Rodriguez-Urrego and Rodriguez-Urrego, 2020). Despite this sudden and extreme drop in travel demand, most activities continued to take place, with people identifying alternatives to continue maintaining their quality of life. Several essential and luxury services and goods were still accessible through crowd-shipping, e-commerce, and remote options (Guthrie at al., 2021). While the pandemic was largely inequitable, impacting marginalized sections of the community more, it was able to highlight that travel demand management would be beneficial in aiding planning agencies reach their carbon emission and congestion reduction goals.

Road pricing is one such proactive travel demand strategy that cities and states have more control over implementing. However, forecasting the impacts, benefits, and revenue of road pricing has historically been challenging in practice. For example, Sydney's Cross City Tunnel has famously struggled financially, attracting only around 30,000 vehicles a day rather than 90,000 estimated during planning (Siddiquee, 2011). Similarly, the developer/operator of Texas's privately-tolled State Highway 130 only narrowly escaped bankruptcy after failing to generate the projected revenue (FHWA, 2024). These examples are only single-facility tolls, and the modeling complexity increases further for variable tolls and congestion pricing (CP) policies applied over a large area. A few different CP strategies have been studied in the literature: 1) Cordon toll, 2) VMT-based fee, 3) Delay-based pricing. Cordon pricing tolls travelers at entry points into a restricted geofence. Scale of implementation is usually limited to a city's central business district (CBD) to target reliable mandatory activities like work trips (for example, London's cordon toll to access downtown during daytime [Transport for London, 2024]). A VMT fee has been proposed recently, that essentially depicts distance-based pricing. Technological barriers limit implementation but the use of satellite systems and advanced 5G coverage is likely to solve this issue as evidenced in Singapore (Singapore Land Transport Authority, 2024). Delay-based pricing tolls the marginal delay an additional roadway user would experience to nudge the transportation system to a system equilibrium. Implementation issues are like that of a VMT-based fee, in addition to the requirement of a stable estimate of congestion for each road link.

The impact of a large-scale implementation of any pricing policy, however, is another unknown when considering a wide array of modal options and integrated travel behaviors. The use of an activity-based framework with feedback from anticipated tolls would capture the impact of decisions right from activity scheduling, mode, and destination choice, to routing during dynamic network assignment. Most studies, however, have focused on network assignment alone for these types of policies. Homogenous or standardized value of travel time (VOTT) is another assumption made in many smaller scale studies in computing generalized travel cost. When moving toward a larger scale implementation, it becomes necessary to include the variability in travelers' VOTT. As VOTT varies by trip type and travelers' socio-demographics, same road users make different choices for mandatory versus discretionary activities, and different road users make different choices based on their threshold to internalize delay (Jiang and Morikawa, 2004). Pricing studies using heterogenous VOTT are few and limited in scope and have been widely suggested as a gap in literature. Capturing such variability in choices becomes paramount before implementing pricing region-wide.

Even when all the modeling aspects of region-wide pricing are captured, the inequities introduced from subjecting all travelers to pricing over and above their vehicle operating costs can introduce inequities (Ecola and Light, 2009). These inequities are also a function of the region's available modal options and traveler socio-demographics. Identifying and correcting for such inequities at the testing stage is crucial.

Contributions

In this study, an agent-based activity-based framework called POLARIS is considered to simulate large regions in relatively low computational time while having the ability to model nuanced pricing policies at the link level and make microscopic traveler decisions. From the literature reviewed, there is a clear and consistent gap of testing the impact of pricing policies in a large-scale setting in a behaviorally consistent way. Furthermore, the impact of different pricing policies, like cordon, VMT-based, delay-based pricing, has not previously been benchmarked against one another on counts of efficiency and equitability in a large-scale setting to the best of the authors' knowledge. This paper aims to bridge that divide and to highlight the comparative benefits and disadvantages of different pricing policies.

Paper Outline

The background section that was just discussed provided the motivation for the work conducted here. The rest of the paper is organized as follows. The literature review section discusses the historical context of CP and relevant research on CP simulations. An overview of POLARIS, including the relevant components and methods used for large-scale simulation of pricing policies, is provided in the methodology section. Details regarding pricing-related formulation and its implementation is also presented in this section. A case study of the region modeled (Austin, TX) is presented after, and provides the scenario setup along with details on revenue-normalization done between pricing scenarios for a just comparison. Results from all the simulations runs are presented next with comparisons between the scenarios studied and associated discussion. The paper ends with conclusions on the results gathered and suggests some future steps.

LITERATURE REVIEW

Congestion pricing and examples of its application

Congestion pricing is an attempt to reconcile the inefficiencies caused by unregulated travel behavior and the resulting externalities by bringing the average costs to the users closer to the actual marginal costs. By charging more for use during peak times and/or in busy locations, it aims to alter people's travel behavior (in terms of route, mode, destination, departure time, activity) so that travel demand can be better satisfied without increasing supply. In first-best tolling, congestion externalities are priced in real-time according to the drivers' VOTT. According to microeconomic theory, this has the effect of maximizing the net social benefit. A driver entering a link is tolled the difference between the marginal social cost (MSC) and average cost (AC), so that the total price paid through the toll and their own travel time is equal to the MSC. However, it is challenging to implement in practice and very unlikely to be socially acceptable. Not only is determining the externalities and VOTT of each road user extremely difficult, first-best tolling requires pricing discrimination due to heterogenous VOTT. Even from a theoretical standpoint, many scholars argue that CP cannot ever be "first-best" (Emmerink et al., 1995; Zhang and Ge, 2004). Specifically, the assumptions about perfect information and rationality weaken as the tolling scheme becomes more complicated. As a result, many practical second-best tolling strategies have been proposed (and some implemented), including cordon, distance-based, and delay-based tolling strategies explored in this study.

While toll roads, bridges, and tunnels have existed for thousands of years, with the primary purpose of raising revenue to cover construction and maintenance costs, the practice of using road pricing to manage system-wide congestion is relatively new. In 1975, Singapore launched the Area Licensing Scheme (ALS) and became the first country to implement CP (Phang and Toh, 2004). Singapore's pricing schemes are examples of cordon toll, which is the most common and basic form of CP. It has been implemented in many cities, including London, Stockholm, and Milan, with different levels of success (Metz, 2018). In recent years, VMT tax or fee has been increasingly discussed, driven by the decrease in fuel tax due to electric vehicles. Also called distance-based tolling, vehicles are tolled by the distance they travel – usually by a flat rate, but the rates can be adjusted by time of day, location, and even vehicle type (de Palma and Lindsey, 2011). Finally, delay-based pricing mimics "first-best" tolling by using best estimates of congestion externality and VOTT. This strategy differs from distance-based tolling in that the tolls are determined individually for each link by estimating the difference between the marginal and average travel costs for many discrete time periods (or sometimes in real time) throughout the day.

Simulations of congestion pricing

While tolls on roads can be easily added to static or dynamic traffic assignment models using assumed VOTT, the traffic assignment model alone does not adequately reflect the full effects of CP policies. First, route choice is not the only choice dimension impacted by CP. Both revealed and stated preference studies have shown that people also alter their departure time and mode selections in response to CP (Yamamoto et al., 2000; Saleh and Farrell, 2005; Karlström and Franklin, 2009). Second, the response to CP varies from person to person (based on their personal and socioeconomic characteristics) and for different trip types. Therefore, it is important to consider heterogeneity, especially in VOTT, when modeling CP. This importance is evident from both theoretical (de Palma and Linsdey, 2004; Koster et al., 2018) and empirical (Yamamoto et al., 2000; Saleh and Farrell, 2005) works.

Several works have combined choice models with traffic assignment models to better model responses to CP policies. Departure time choice is most commonly investigated due to the high interest in analyzing the peak spreading effect of time-dependent CP. For example, Adoudina et al. (2016) proposed a framework for incorporating departure time choice to a dynamic traffic assignment (DTA) model. Their approach involves updating the temporal demand pattern input to the DTA module according to a heteroskedastic generalized extreme value-based departure time choice model. Using their proposed framework, the authors compared flat and variable tolling for Gardiner Expressway in Toronto, Canada, and found that variable tolling was more effective thanks to departure time rescheduling, while flat tolling led to excessive rerouting that ended up blocking access to the toll road during peak hours. Lentzakis et al. (2020) supplemented a DTA model with a pre-trip behavioral model, which allowed for mode changes (from car to public transit) and trip cancelations, in addition to changes in route and departure time, in response to tolling.

In recent years, agent-based simulations have become increasingly adopted by researchers for travel demand modeling. Agent-based simulations are especially well-suited for testing CP policies, as it inherently addresses the two aforementioned problems in the traffic assignment-only approach. The integrated demand-supply modeling framework allows for the impacts of pricing schemes to be captured across multiple choice dimensions, including route, departure time, mode, and destination, and the agents can be synthesized with realistic heterogeneity. Furthermore, the planning and execution trips by agents can be tracked, allowing for much more detailed welfare and equity analyses. Several CP studies have already been conducted using agent-based simulations, although user heterogeneity is not always fully implemented. He et al.'s (2021) MATSim-NYC model indicated more than twice as much reduction in car trips as result of the cordon tolls proposed for New York City (City of New York, 2024) than predicted by the Regional Plan Association. Simoni et al. (2019) also used MATSim to explore CP in the age of autonomous vehicles (AVs) with both personal AVs and SAVs and mixed traffic and found that the composition of the vehicles (AV vs SAV) in the network influences the effectiveness of CP policies. Similarly, Gurumurthy et al. (2019) revealed that SAVs fleets with dynamic ride-sharing (DRS) perform better under a peak travel-time based CP strategy, decreasing VMT and increasing profits despite the tolls thanks to increased demand. Jing et al. (2024) evaluated distance, cordon, and area-based CP using SimMobility, another agent-based simulation framework with a toll-sensitive freight model, and found that low-income individuals and small businesses suffer under the CP policies.

METHODOLOGY

The large-scale study of different pricing policies requires an agent-based activity-based approach to be able to modify intricate details for pricing and model detailed traveler behaviors. With all parts of the model represented by agents, results are available in robust detail and enables thorough analysis for any pricing policy. The agent-based activity-based framework used in this study is called POLARIS (Auld et al., 2016).

At a high level, POLARIS can be described as the joint execution of the following steps: population synthesis, activity generation and scheduling (including mode and destination choices), and routing and traffic flow simulation. Population synthesis is region-specific and, for U.S.-based models, sources data from the Census, American Community Survey, and Public Use Microdata Sample. Using iterative proportional fitting, a pre-defined sample of the region's household and person population can be synthesized, with POLARIS supporting computation of 100% samples for several large-scale regions. Activity generation and scheduling in POLARIS follows closely to previous research by Auld and Mohammadian (2009, 2012). Activities are generated following a distribution for different person types in the modeled region. A destination choice model selects a random subset of available destination locations in the model filtered by trip type and constructs a multinomial logit structure to pick the destination with the highest utility (Auld and Mohammadian, 2011). This incorporates travel costs for auto and transit modes and can capture the anticipated tolls for any pricing policy. Another nested choice model then forecasts chosen mode with trip start, origin and destination known. Key variables in the nested choice model include the mode-specific estimated travel time, cost, and access time, and associated VOTT derived as a function of household income and trip purpose (across classical definitions of home-based work, home-based other, and non-home based trips). Once activities are planned for the day, activities and trips are scheduled to be executed through the traffic flow simulation (de Souza et al., 2019) using time-dependent A* shortest paths (Verbas et al., 2018). An agent-specific router uses a key input of VOTT which is used to determine and minimize the generalized travel cost for the entire trip. Incorporating heterogenous VOTT in the router is key in determining the response by different income segments and trip types. POLARIS records link information for each minute of the simulation, including volume, queue length, and travel time.

Road Pricing Strategies

The objective of this study is to benchmark various pricing policies using a single framework, along the lines of region-wide impact and equity implications. Pricing policies like a CBD cordon toll, distance-based fees, and delay-based CP were implemented in POLARIS. Link-level time-dependent tolls is an input to the A* algorithm when finding shortest paths. These toll tables were constructed by link and time period according to the pricing policy, for use during simulation runtime. Executed trips store tolls paid at the trip level, but this is also stored in the skims after aggregating it at the origin-destination zone indices and relevant skim period. Across multiple executions of POLARIS, the method of successive averages is used to obtain a stable skim that is a function of demand. Since these skims impact choices made during the activity generation and scheduling phase, a stable skim is pivotal when inferring results. As the levied tolls significantly change skims in the initial rounds of execution when travelers are learning to make decisions, several iterations of POLARIS are simulated before results are reported.

Central-Business District Cordon Toll

Most mandatory and consistent trip-making happens to and from the CBD for work. The pandemic has impacted this a little, leaving several buildings mostly empty, but the demand into the CBD is generally on the rise (Sun et al., 2019). Devising a cordon toll for entry (or exit, or both) into the CBD can help alleviate some congestion within City centers. This is primarily done to incentivize use of transit or other modes into CBD. Cordoned areas are region dependent and the effectiveness rests solely on the design and cost. While varying cordon tolls at different entry points can manage demand and revenue more flexible, a simple cordon toll is levied on all links leading into the CBD in this study. There is no charge to leave the CBD.

Distance-Based (VMT) Fee

Distance-based or VMT fees is a way to toll drivers for their use of the roadway system. Each link in the network is subject to the same toll per unit distance regardless of the time of day. This strategy has garnered attention in recent years as a way to replace or supplement falling gasoline tax revenue with the advent of electric vehicles. This policy has the effect of minimizing network VMT, but may increase network-wide VHT and congestion as drivers flock to shortest paths. In this study, the distance-based fee strategy is implemented as a flat per-mile toll on all links in the network.

Delay-Based Congestion Pricing

Past research has shown the effectiveness of marginal-cost CP (Li et al., 2021). Considering traveler delay on each link to identify the marginal cost to levy on the additional traveler choosing to enter that link at that time of day, can incentivize these travelers to find alternate routes that may be longer. In theory, this policy has the effect of minimizing network-wide VHT and may or may not increase system VMT. This depends on the alternate mobility options available to completely avoid the toll when considering a particular point in the origin-destination-time prism. The toll levied on a link is determined as follows, with iterative feedback between iterations of POLARIS using a Python program:

$$\tau_{l,i,t} = w_C \,.\, d_{l,i,t} \,.\, p_{delay} + w_I \,.\, \tau_{l,[i-1],t} + w_T \,.\, \tau_{l,i,[t-1]} \tag{1}$$

where $\tau_{l,i,t}$ is the toll on link l during period t calculated after iteration i. $d_{l,i,t}$ is the average delay, which is the difference between the experienced and free flow travel times in the mesoscopic traffic flow model with Lagrangian coordinates calculated over the time interval t (de Souza et al., 2019; de Souza et al., 2024). The traffic model in POLARIS uses the triangular fundamental diagram, and the delay can be interpreted as the lower bound estimate of the average difference between the marginal and average costs of the vehicles on the link, since queue order is not considered for pricing. p_{delay} is the average cost per delay and should be set an estimate of the average VOTT. $\tau_{l,[i-1],t}$ is the link toll calculated in the previous iteration for the same time period, and $\tau_{l,i,[t-1]}$ is the link toll for the previous time period calculated during the current iteration. w_C, w_I, and w_T are weights and were set to 0.6, 0.2, and 0.2, respectively, in this study.

AUSTIN APPLICATIONS

This study compares the effects of cordon, distance-based, and delay-based CP strategies in the 6-county region of Austin, Texas, for a typical weekday using the Capital Area Metropolitan Planning Organization (CAMPO) network for the forecast year 2035 (Figure 1) and a 25% sample synthesized population. A scenario with no tolls is used as the baseline. In the cordon toll scenario, entrance into Austin's core, which was demarcated by 38th Street in the north, Cesar Chavez Street in the south, Interstate 35 in the east, and MoPac Expressway in the west (Figure 2), was tolled at 56 points along the cordon from 7 AM and 6 PM, as in London (Transport for London, 2024). Under distance and delay-based pricing, all links in the network were tolled, assuming access to a satellite-based technology that allows for the efficient and accurate tracking of routes taken by individual vehicles, as in Singapore. An average VOTT of $18 per hour ($0.05 per second of delay) was assumed for setting the delay-based tolls, which were varied every 15 minutes (Simoni et al., 2019). The per-mile delay-based toll was capped at $5 per mile. To provide a useful comparison, tolls for distance-based pricing were iteratively set to generate the same amount of revenue as the delay-based pricing. The target revenue of the cordon toll was set to the delay-based pricing revenue scaled by the fraction of auto trips entering the cordon in the baseline scenario.

Figure 1. 2035 Six-County Austin Road Network (42,043 lane-miles)

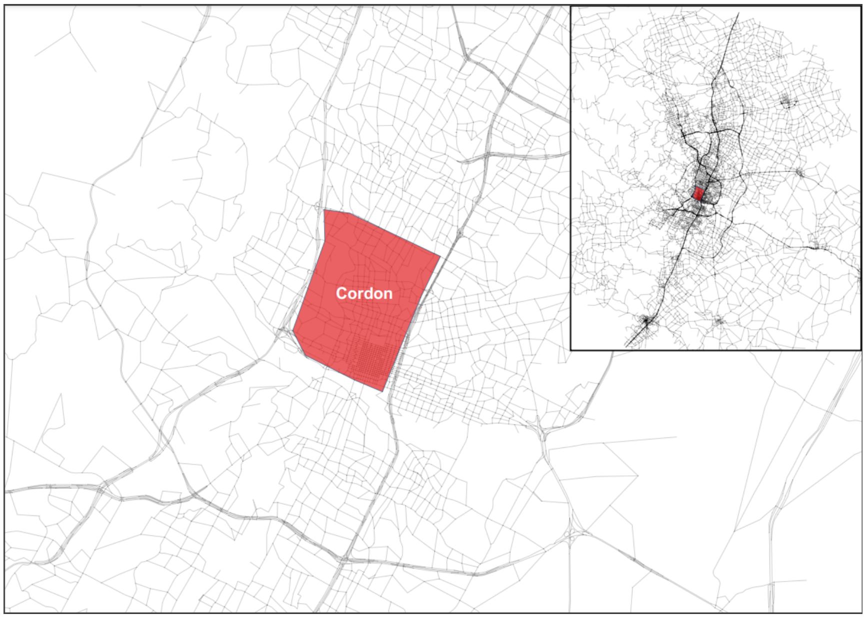

Figure 2. Cordon tolling around Austin's Core (38th Street to Cesar Chavez, MoPac and IH35)

RESULTS

Table 1 presents an overview of the simulations results scaled up to 100% population. Compared to the baseline scenario with no tolls, the delay-based, distance-based, and cordon CP strategies reduced VMT by 1.6, 3.6, and 0.2%, respectively. The reductions in VHT were more substantial at 10.3, 5.6, and 1.1%, respectively. Delay-based pricing raised \$4.06 M per day, which averages to \$1.37/person per day or \$0.51 per vehicle-trip. This is considerably more than \$1.2 M that would be collected from gasoline tax at approximately \$0.02 per mile. The tolls for the distance-based were iteratively set to generate a similar amount of revenue as the delay-based pricing, resulting in a VMT fee of \$0.09 per mile. As expected, distance-based pricing led to the most reductions in VMT, while VHT reduction was greatest under delay-based pricing. Under the baseline scenario, 18.6% of auto trips entered the cordon. Therefore, the target toll revenue of the cordon tolls was set to \$744,000 per day, leading to a \$4.83 toll when entering the Austin's core (Figure 2) between 7 AM and 6 PM. Table 1 also shows the total delay hours, defined as the cumulative time spent on the network by vehicles above the link free flow travel times. This metric can be interpreted as hours lost to congestion every day. Both delay- and distance-based pricing led to tangible reductions in delay hours at 36.3% and 12.6%, respectively, from the baseline. However, the ratio of total delay hours to VHT in the distance-based pricing scenario (21.7%) is only slightly lower than that of the baseline (23.5%), while it falls substantially under delay-based tolling (16.7%). Additionally, the delay-based pricing scenario saw a 6.6% increase in average speed on the network from the baseline, while the boost in speed was more modest in the distance-based pricing scenario at 1.8%. This suggests that while delay-based tolling is improving network efficiency, the reductions in total delay hours for the distance-based tolling scenario mostly comes from reductions in the distances driven. Cordon tolling had negligible impact on network VMT and VHT and did not lead to significant reductions in total delay hours nor improvements in average speed in the network. Figure 3 is the network loading curve (scaled up to 100% population) showing the number of vehicles in the network during each minute of the simulation under each pricing strategy. There is a noticeable reduction in the number of vehicles in the network during the AM and PM peaks for delay-based pricing and a slight reduction in the PM peak volumes for distance-based pricing, while the curve for cordon pricing nearly overlaps that of the baseline scenario.

Table 1 Aggregate summary of results across four pricing scenarios

Scenario	**VMT (miles per weekday)**	**VHT (hours per weekday)**	**Toll Revenue (in $/day)**	**Total delay hours**	**Average speed (mph)**
Baseline	60.5 M	2.19 M	$0	514 K	28.1
Delay-based pricing	59.5 M	1.96 M	$4.06 M	328 K	30.5
Distance-based pricing	58.3 M	2.07 M	$3.92 M	450 K	28.6
Cordon pricing	60.4 M	2.17 M	$0.74 M	504 K	28.2

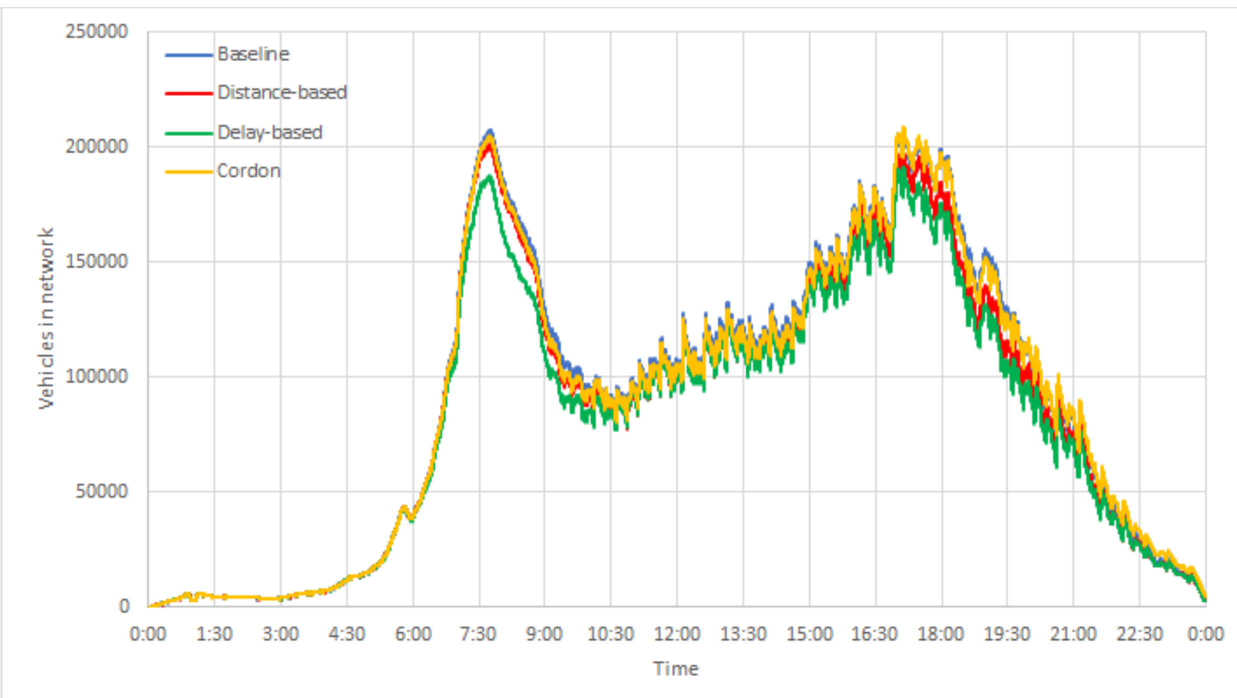

Figure 3. Network loading curve

Figure 4 illustrates the change in departure time choice as the % change in the number of trips started in each hour. While little change was seen in the distance-based and cordon pricing scenarios, significant shifts in trip start times were observed in the evening as a result of delay-based pricing. Interestingly, the shift is towards the peak rather than having a peak-shaving effect. Departures during the peak hours of 5-7 PM rose by 4.7%, while departures 7 PM onwards fell by 6.4%. This is likely because the reduction of delay allows more travelers follow their preferred activity start time.

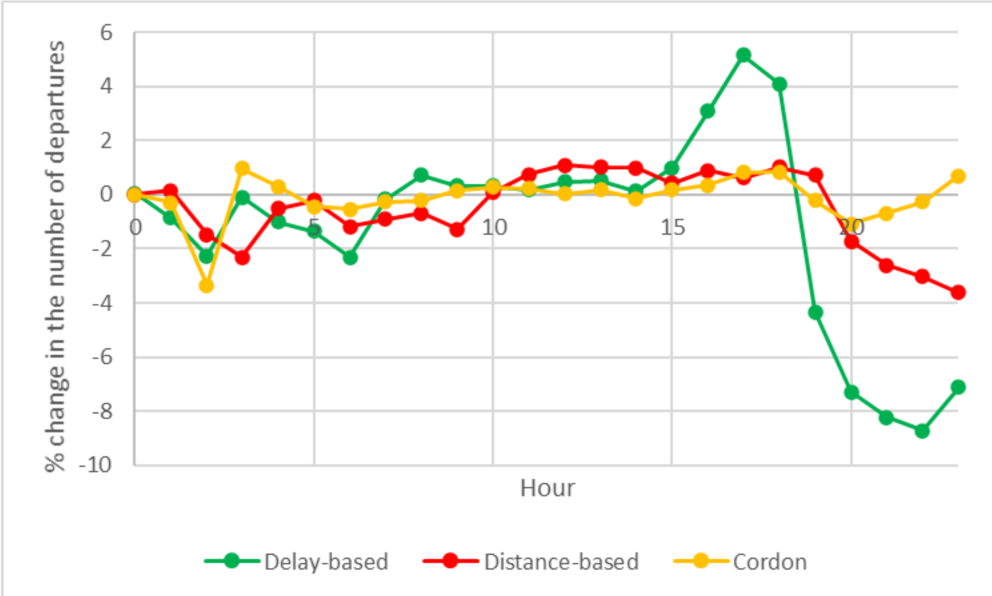

Figure 4. Percent change in the number of departures in each hour

Changes in mode share was negligible for the case of Austin. The share of person trips taking place in a private vehicle in the baseline scenario was 92.5% and reduced by less than 0.2 percentage points for all three CP scenarios. The vehicle occupancy did not increase either, only reducing the number of vehicle trips by less than 0.5%. This is likely due to the lack of public and active transport options in Austin. It should also be noted here that the total number of trips across all modes experienced no change across the scenarios.

Table 2 shows the change in the average travel distance to key activities. Under delay- and distance-based pricing scenarios, discretionary trips saw reductions in the distance traveled, while travel distances to work trips remained largely unchanged. The reductions were greater for distance-based pricing, in which the average travel distances to discretionary activities were about 6-7% less than those of the baseline However, it is unclear how much of these travel distance reductions can be attributed to destination choice versus route choice (i.e., choosing a closer destination vs taking a more direct route). Unlike delay- and distance-based tolling, cordon tolling had little impact on the average travel distances to activities. Table 3 shows the shows the change in the average travel distance to the same activities. Under delay-based pricing, the percentage reductions in travel times are more than double those of travel distances shown in Table 2. Travel time reductions were the greatest for full-time work trips at 9.45%, even though work trips had no change in travel distance, indicating a considerable decrease in network delays. However, under distance-based pricing, travel time fell by lesser margins than travel distances for all activities other than work. This again suggests that most of the VMT and VHT reductions under distance-based pricing likely come from travelers opting for closer (and less ideal) destinations and that the strategy is relatively inefficient at improving network performance.

Table 2. Changes in average travel distance to activities

	Baseline	Delay-based	Distance-based	Cordon

Activity	Average travel distance (mi)	Average travel distance (mi)	% change from baseline	Average travel distance (mi)	% change from baseline	Average travel distance (mi)	% change from baseline
Work (full-time)	13.6	13.5	-0.50	13.4	-1.21	13.6	+0.27
Work (part-time)	13.9	13.9	-0.17	13.8	-0.90	13.9	-0.01
Eating out	8.1	7.9	-2.49	7.6	-5.80	8.1	-0.58
Personal	7.2	7.0	-2.31	6.8	-5.66	7.2	+0.28
Religious/civic	7.5	7.3	-3.00	7.0	-6.53	7.5	-0.55
Service	7.0	6.9	-2.43	6.6	-6.59	6.9	-1.35
Shopping (major)	7.9	7.7	-2.73	7.3	-7.01	7.9	-0.45
Shopping (other)	7.0	6.8	-2.13	6.6	-5.94	7.0	-0.25
Social	8.8	8.5	-3.32	8.2	-6.93	8.7	-0.38

Table 3. Changes in average travel time to activities

	Baseline	Delay-based		Distance-based		Cordon	
Activity	Average travel time (minutes)	Average travel time (minutes)	% change from baseline	Average travel time (minutes)	% change from baseline	Average travel time (minute)	% change from baseline
Work (full-time)	20.7	18.7	-9.45	20.1	-2.66	20.4	-1.41
Work (part-time)	20.3	19.0	-6.58	19.8	-2.54	20.1	-1.11
Eating out	14.5	13.6	-6.27	13.9	-4.17	14.4	-0.44
Personal	11.7	10.9	-6.20	11.1	-4.73	11.7	+0.33
Religious/civic	12.5	11.6	-7.07	11.9	-4.42	12.4	-0.27
Service	11.3	10.6	-6.13	10.7	-5.17	11.1	-1.99
Shopping (major)	12.8	11.9	-6.56	12.1	-5.64	12.7	-0.29
Shopping (other)	12.0	11.3	-5.62	11.5	-4.29	12.1	+0.54
Social	14.5	13.2	-8.47	13.6	-5.94	14.4	-0.10

Delay-Based Congestion Pricing

Figure 5 shows the average toll in the network weighted by link lane-miles during each 15-minute interval under delay-based pricing. The shape of the curve closely mimics that of the network loading curve in Figure 3. The average per lane-mile toll tops out at approximately \$0.07 during the peak, which is less than the \$0.09 per mile toll needed on all lanes in all links throughout the day in distance-based pricing to generate the same revenue. Figure 6 illustrates the spatial distribution of tolls during the AM and PM peak periods. For bidirectional links (which are most links), the more expensive direction is depicted. The tolling patterns are similar for the two peak periods, with heavy tolling in the central area and virtually no tolls on the outer links of the network.

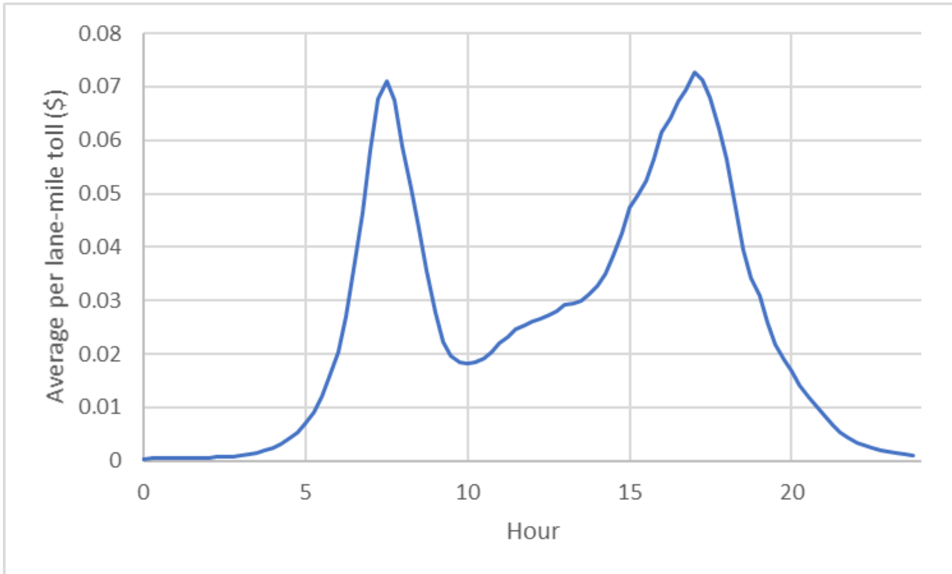

Figure 5. Average per lane-mile toll under delay-based pricing

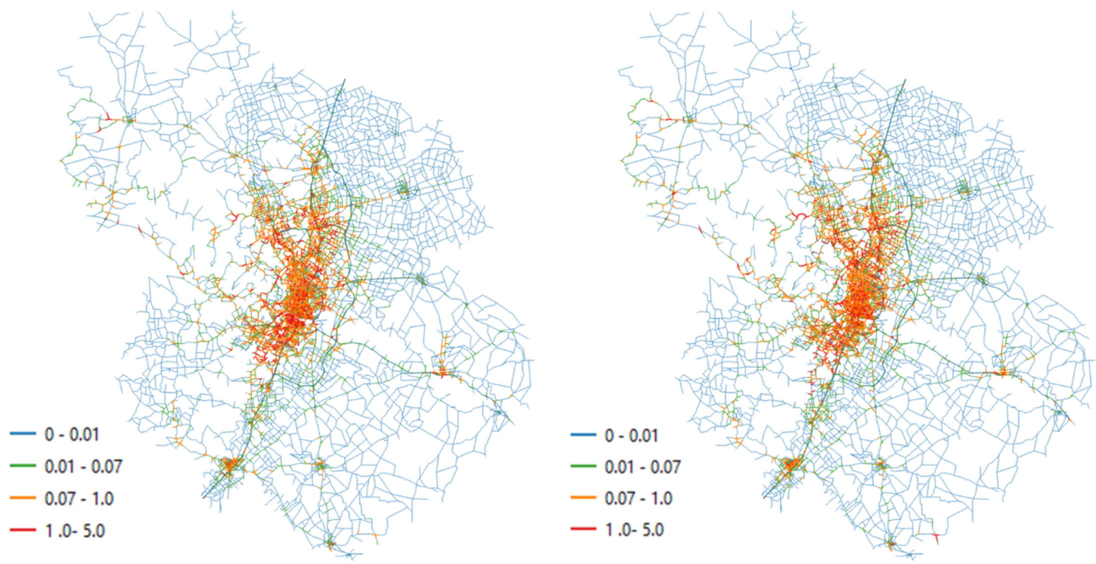

Figure 6. Per-mile toll during AM peak (7:30 – 7:45 pm) and PM peak (5:00-5:15 pm) under delay-based pricing on Austin's 2035 network

Equity

In order to assess the equity implications of the CP strategies, the spatial disparities in the impacts were investigated. Figure 7 shows the average daily tolls paid per resident in each traffic analysis zone (TAZ) in the delay- and distance-based tolling scenarios. Even though the total toll revenue collected across the individuals living in the Austin 6 county region are the same in the two scenarios, the spatial distributions of the toll burden are starkly different. Under delay-based pricing, people living near the core of the region (where the links are more congested and tolled at higher rates as shown in Figure 6) pay above $2 per day. Conversely, under distance-based pricing, people living in the outer rural zones face higher daily tolls, as they travel further distances than those living in the city center for their daily activities.

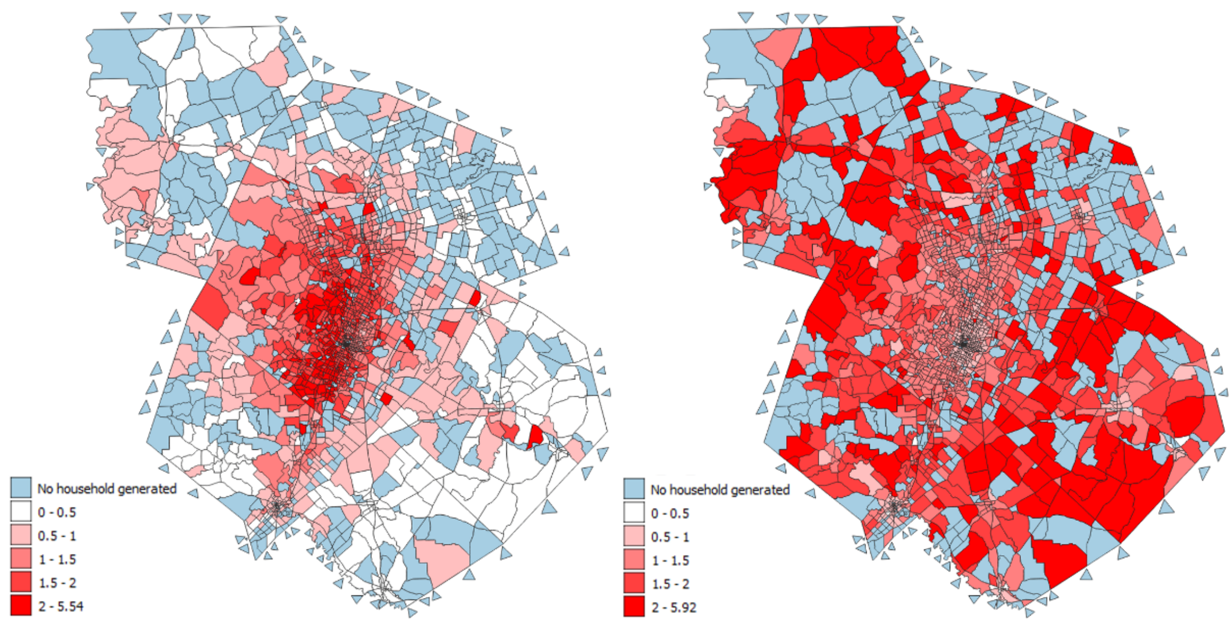

Figure 7. Average daily toll paid per person by TAZ of residence under delay- (left) and distance-based (right) tolling

CONCLUSIONS

This study applied cordon, distance-based, and delay-based tolling strategies to Austin, Texas, using the POLARIS agent-based activity-based travel demand simulation model. All three CP strategies led to decreases in both network VMT and VHT but to different degrees. As expected, distance-based pricing had the greatest reduction in VMT at 3.6%, while the largest VHT reduction of 10.3% was observed in the delay-based pricing scenario, and both tolling strategies yielded tangible reductions in network delay hours. Although strong evidence of network efficiency improvements is seen with delay-based tolling, the perceived benefits under distance-based pricing primary stem from reductions in the distances driven. Therefore, all-day flat-rate distance-based tolling is likely not ideal from a social acceptability and welfare standpoint. Incorporating zone- or time-based rates may alleviate some of the inefficiencies of distance-based tolling. Cordon pricing in the core Austin area, generating a revenue proportional (in terms of trips affected) to the other two strategies, had little impact on overall network performance. This suggests that higher rates are likely needed to cause changes in congestion patterns in the network. Further effects of the three CP policies were analyzed with regards to the choice dimensions of departure time, mode, destination, and route, and mode. Interestingly, the delay-based pricing strategy elicited travelers to shift towards the PM peak, rather than away from it, as decrease in network delay allowed more people to realize their preferred activity start times. Under delay-based pricing, people can enjoy travel time reductions for all types of activities without having to shorten their trip distances by much or at all. Conversely, under distance-based pricing, travel time savings are subpar to the reductions in travel distances, again demonstrating the inefficiency of the strategy. No significant mode shifts or increases in vehicle occupancies were observed across scenarios, suggesting CP will not be impactful in promoting public transit, non-motorized modes, or car-pooling in the car-centric context of Austin. Lastly, the amount of toll paid per person per day differs greatly by residential location and between delay- and distance-based tolling. Residents of central Austin incur the highest tolls under delay-based pricing, while those in outer areas pay the most under distance-based pricing. This is crucial consideration for understanding equity implications, social acceptability, and potential impacts on land use.

Although this study provides insights into the impacts of various second-best tolling strategies in a large network, there are certain limitations that warrant consideration. First, as cordon tolls have a more local objective of reducing congestion inside the cordon, as opposed to network-wide reductions by delay- and distance-based tolling, further analysis should be conducted on tolling effects inside the cordon. Furthermore, future work should further investigate equity and social welfare implications and ways to correct for inequities, such as credit-based congestion pricing (CBCP), which aims to return profits from road pricing through travel credits for transit or another mode of transport (Kalmanje and Kockelman, 2004). Finding an equitable way to distribute these credits is still a point of debate, but even the act of returning profits has shown to boost the efficiency of CP and mellowing the political debate of whether pricing for public infrastructure is acceptable.

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