COMPARING DELAY-, DISTANCE-, AND CORDON-BASED CONGESTION PRICING STRATEGIES VIA LARGE-SCALE SIMULATION

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ABSTRACT

This study compares the impacts of cordon, distance-based, and delay-based congestion pricing strategies for Austin, Texas, using the POLARIS agent-based activity-based travel demand simulation model, examining 18 scenarios. This approach enables agent-level heterogeneity and realistic choice options (including destination and mode) for dynamic assignment and congestion feedbacks across a major metro region, which are features lacking in past work. To ensure comparability, distance-based tolls were set to generate the same revenue as delay-based tolling of $3.5 M/day, averaging $1.15/resident/day or $0.42/vehicle-trip. Delay-based pricing eliminates 44% of network delay, which accounts for 25% of VHT in the no-tolling baseline scenario. Distance-based pricing is the most effective at reducing VMT (by 4%), but delay reductions are limited, primarily stemming from decreases in the distances driven. Results from various implementations of delay- and distance-based pricing suggest that spatial variations of tolls are more important than temporal variations. Cordon tolls of $0.50 to $0.60 (delivering revenues-per-baseline-trip equivalent to the other two strategies) have little effect but deliver notable impacts when tolls are greatly increased. Other major findings include: 1) delay-based pricing shifts travelers toward the PM peak instead of having a peak-shaving effect; and 2) tolls' spatial impacts, including changes in network flows and tolls paid by residents, vary substantially between delay- and distance-based pricing strategies.

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 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 U.S. Department of Transportation (USDOT) suggests that most travel in the U.S. 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 can simply shift the bottlenecks or impose marginally lower delays on a wider segment. While infrastructure is the cornerstone of productivity, an excess of it does not guarantee multifold benefits. 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 U.S. for some time now.

Road pricing is another 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 proved challenging. For example, Sydney's Cross City Tunnel has famously struggled financially, attracting only around 30,000 vehicles a day rather than the 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) marginal cost CP. Cordon pricing tolls travelers at entry points into a restricted geofence. The scale of implementation is usually limited to a city's central business district (CBD) to target reliable mandatory activities like work trips and reduce through traffic (e.g., London's cordon toll to access downtown during daytime [Transport for London, 2024]). VMT fees have been proposed recently as a solution to declining gas tax revenues. 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). Marginal cost CP tolls the difference between the marginal social cost (MSC) and the travel time to nudge the transportation system toward the system optimum. 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. VOTT generally varies by trip type and travelers' demographics, meaning the same road user makes 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 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 used to simulate a large region in a relatively low computational time, modeling nuanced link-level pricing policies and 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, and delay-based pricing, has not previously been benchmarked against one another on counts of efficiency and equitability in a large-scale setting. This paper aims to bridge that divide and to highlight the comparative benefits and disadvantages of different pricing policies.

LITERATURE REVIEW

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, and activity) so that the region's travel demand can be better satisfied without increasing supply. In first-best tolling, congestion externalities are priced in real-time according to the drivers' willingness-to-pay. 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, uncertainties in the VOTT of road users and the valuation of other externalities (such as emissions and noise) make first-best pricing challenging to implement. 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.

Although 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 area toll is a variation of the cordon toll, which is the most common and basic form of CP. It has subsequently 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 revenue 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 the best estimates of congestion externalities and VOTT. This strategy differs from distance-based tolling in that the tolls are determined individually for each road segment 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 can be easily added to static or dynamic traffic assignment models using assumptions of VOTT, traffic assignment models alone do 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 studies have combined choice models with traffic assignment models to better model responses to CP policies. Among the possible additional choice dimension to incorporate, departure time choice is the most commonly investigated due to the strong interest in analyzing the peak spreading effect of time-dependent CP. For example, Adoudina et al. (2016) proposed a framework for integrating departure time choice into 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. The authors compared flat and variable tolling for the 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 changes in mode (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 they inherently address the two critical issues found in traffic assignment-only approaches. First, the integrated demand-supply modeling framework captures the impacts of pricing schemes across multiple choice dimensions, including route, departure time, mode, and destination choices. Second, agent-based models incorporate realistic heterogeneity, capturing individual- and trip-specific differences in behavioral responses to CP policies. Furthermore, the planning and execution of trips by agents can be tracked microscopically, allowing for more detailed welfare and equity analyses. Several studies on CP have used agent-based simulations, although user heterogeneity is not always fully implemented. He et al. (2021) found that their MATSim-NYC model predicted more than twice the reduction in car trips due to the cordon tolls proposed for New York City (City of New York, 2024) compared to the predictions made by the Regional Plan Association. Simoni et al. (2019) also used MATSim to explore CP in the era of autonomous vehicles (AVs), including both personal AVs and shared AVs (SAVs) in mixed traffic with conventional vehicles. Their study found that the composition of vehicles in the network affects the effectiveness of CP policies, leading to varying policy recommendations. Building on this work, Gurumurthy et al. (2019) found that SAVs fleets with dynamic ride-sharing (DRS) perform better under a peak travel-time based CP strategy. This approach decreased VMT and increased profits despite the tolls, thanks to the increased demand. Jing et al. (2024) used SimMobility, an agent-based simulation framework with a toll-sensitive freight model, to evaluate distance, cordon, and area-based congestion pricing (CP) policies. Their findings indicate that these CP policies disproportionately impact low-income individuals and small businesses. Finally, Vosough et al. (2022) used the METROPOLIS dynamic traffic network simulator to study cordon tolling in a fictional radial city with a focus on pricing emissions. They modeled departure time, mode, and route choices, as well as the dispersion of particulates by wind.

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; (de Souza et al., 2024) 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. CBD cordon toll, distance-based pricing, and delay-based CP were implemented in POLARIS. Link-level, time-dependent tolls, determined by the pricing policy, are considered by the A* algorithm when finding shortest paths. Additionally, these tolls are reflected in the network skims after being aggregated at the origin-destination zone indices and relevant skim periods. Tolls paid during executed trips are also recorded. Across multiple executions of POLARIS, the method of successive averages (MSA) 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.

Cordon Toll

Most mandatory and consistent trip-making happens to and from the CBD for work. Devising a cordon toll for entry 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, as well as reduce through traffic. Cordoned areas are region dependent and the effectiveness rests solely on the design and cost. Area tolls (in London, Stockholm, Singapore, and now Manhattan) allow for multiple entries and are more common in practice but less impactful than a cordon toll. While varying cordon tolls at different entry points can manage demand and revenue more flexibly, 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 Pricing

Distance-based pricing or VMT fee is a way to toll drivers for their use of the roadway system. In its most basic implementation, 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 aims to reduce network-wide VMT but may increase VHT and congestion as drivers flock to more direct paths. In this study, the basic distance-based fee strategy is implemented as a flat per-mile toll on all links in the network, but adjustments by time of day (TOD) and location are also examined.

Delay-Based 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 toll (MCT) to levy on travelers choosing to enter that link depending on time of day can incentivize these travelers to find alternate routes are less congested. 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 avoid high tolls when considering a particular point in the origin-destination-time prism.

After each iteration, the average delay experienced by vehicles on a link during a time interval can be priced using an estimate of the average VOTT. When applying the economic principle of marginal cost CP to static user equilibrium, this value serves as the lower bound estimate of the marginal external cost (i.e., $c(Q) - c(0) \leq c'(Q)Q$ where $c(\cdot)$ is the cost function and Q is the flow), because the link performance function is convex. However, directly applying this economic concept to dynamic traffic assignment (DTA) poses some challenges. Namely, fundamental diagrams allow for two different travel times for the same flow, and congestion can arise from conditions downstream instead of the flow on the link itself. In a DTA model with more realistic traffic flow dynamics, the optimal MCT can be obtained by splitting the link into normal flow (below capacity) and forced flow (above capacity) segments (Yang and Huang, 1998; Jing et al., 2024). The economic analytical marginal cost formulation is applied to the flow-speed-density relationship under normal flow, while queueing delay represents marginal external cost under forced flow.

POLARIS's link model uses a triangular fundamental diagram, meaning it assumes free-flow conditions for subcritical densities (de Souza et al., 2019). Therefore, link travel times increase only due to queueing. Let $x_{ij}(t)$ be the number of vehicles exiting link (i, j) at time t (which is discrete), $\tau_{ij}(t)$ be the link travel time experienced by vehicles exiting link (i, j) at time t, and $y_{ij}(t)$ be the clearance rate of the queue at the downstream end of link (i, j) at time t. According to Boyles et al. (2024, p. 435), if $y_{ij}(t)$ is less than the sending flow $S_{ij}(t)$, the link is considered supply constrained, and

$$\frac{\tau_{ij}(t)}{dx_{ij}(t)} = \frac{1}{y_{ij}(t)} \tag{1}$$

In this case, the marginal social cost is:

$$MSC_{ij}^{\,t} = \frac{dx_{ij}(t)\tau_{ij}(t)}{dx_{ij}(t)} + \frac{\left(l_{ij}(t) - x_{ij}(t)\right) d\tau_{ij}(t)}{dx_{ij}(t)} = \tau_{ij}(t) + \frac{l_{ij}(t)}{y_{ij}(t)} \tag{2}$$

where $l_{ij}(t)$ is the total queue length including vehicles joining this queue in future timesteps. Therefore, drivers traversing link (i, j) and exiting at time t should be tolled

$$MCT_{ij}^{\,t} = \overline{\beta}_{ij}(t) \cdot \frac{l_{ij}(t)}{y_{ij}(t)} \tag{3}$$

where $\overline{\beta}_{ij}$ is the average VOTT of the drivers in the queue (Mayet and Hansen, 2000). Now consider a vehicle randomly inserted at the downstream end of link (i, j) sometime during time interval (t_1, t_2) according to the temporal distribution of $x_{ij}(t)$. Then, the expected MCT is:

$$E\left(MCT_{ij}^{\,(t_1,t_2)}\right) = \frac{\sum_{t\epsilon(t_1,t_2)} \overline{\beta}_{ij}(t) \cdot \frac{l_{ij}(t)}{y_{ij}(t)}\, x_{ij}(t) \left[y_{ij}(t) < S_{ij}(t)\right]}{\sum_{t\epsilon(t_1,t_2)} x_{ij}(t)} \tag{4}$$

This shows that the exact expectation of MCT can be obtained if the $x_{ij}(t)$, $y_{ij}(t)$, $S_{ij}(t)$, $l_{ij}(t)$, and $\overline{\beta}_{ij}(t)$ are recorded for every network loading timestep. However, the timesteps used in DTA, which normally range from 1 to 10 seconds (1 second in this study), makes this challenging to implement. Therefore, in this study, we use the following approximation of the expected MCT, which we call delay-based toll:

$$E\left(MCT_{ij}^{\,(t_1,t_2)}\right) \approx \overline{\beta} \cdot \frac{\sum_{t'\epsilon(t'_1,t'_2)} \overline{d}_{ij}(t')\, x_{ij}(t')}{\sum_{t'\epsilon(t'_1,t'_2)} x_{ij}(t')} \tag{5}$$

where $\overline{d}_{ij}(t')$ is the average link delay experienced by vehicles exiting link (i, j) at time t'. We use t' here instead of t to show that the time discretization need not be the network loading timesteps. Instead, the timesteps at which $\overline{d}_{ij}(t')$ and $x_{ij}(t')$ are recorded should be used (1 minute in this study). Furthermore, from an equity standpoint, changing the unit toll (per delay-second) as a function of socioeconomic characteristics of travelers on the road may not be preferable, so we used a single average VOTT. Based on these calculated values, the link-level, time-dependent tolls can then be updated between iterations through MSA. A similar delay-based approach has been used by Simoni et al. (2019), although the link delays were calculated based on its own flow and density without regards to downstream dynamics. This approach can also work as a heuristic for other fundamental diagrams (e.g., Greenshield) by combining delays across normal and forced flow segments, drastically simplifying the computation. In the DTA model, this formulation can represent either static tolls based on average conditions or average dynamic tolls based on real-time predictions.

AUSTIN APPLICATION

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% synthetic population. A scenario with no tolls is used as the baseline. Two cordon sizes are used for cordon tolling: The smaller cordon is demarcated by 38th Street to the north, Cesar Chavez Street to the south, Interstate 35 to the east, and MoPac Expressway to the west, containing 56 tolling points. The larger cordon has U.S. Highway 183 on the north and west, Texas State Highway 71 to the south, and MoPac Expressway to the west, with a total of 92 tolling points. Cordon tolling is enforced from 7 AM to 6 PM, as in London (TfL, 2024). Under distance and delay-based pricing, all network links are 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. For delay-based pricing, the average VOTT is calculated from the trip records of passenger vehicle drivers in the baseline scenario, weighted by travel distance. Various time intervals were) tested to adjust the tolls, with the per-mile delay-based toll capped at $5. In addition to the flat per-mile toll, three variants of distance-based pricing were tested: time-of-day-adjusted pricing, location-adjusted pricing, and the combination of both. 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 base 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. Further impacts of cordon tolls were investigated with additional simulations with revenue multipliers. The simulations were conducted on the Texas Advanced Computing Center's Lonestar6 high-performance computing system, utilizing 24 threads on 1 node equipped with 2x AMD EPYC 7763 64-Core Processors and 256 GB (3200 MT/s) DDR4 RAM. Each 24-hour day simulation iteration took 1.25 hours on average.

Figure 1. CAMPO's 2035 6-County Austin Road Network (42,043 lane-miles) with Small Cordon in Red (38th Street, IH35, Cesar Chavez, and MoPac) and Large Cordon in Blue (US183, SH71, and MoPac)

RESULTS

Here, the delay-based pricing results are presented first, because the level of tolls used in the distance- and cordon-based scenarios are designed to deliver similar revenues.

Delay-Based Pricing

Table 1 presents an overview of the baseline and delay-based pricing simulations results scaled up to 100% population. The baseline scenario with no tolling yielded a VMT of 60.1 M miles per day and a VHT of 2.17 M hours per day, of which nearly a quarter was due to congestion delays. The average VOTT from the baseline scenario, $12.40 per hour, was used to calculate the link- and time-specific delay-based tolls according to Equation (5). Details of the VOTT distribution are provided in Appendix A. The delay-averaging or toll-changing interval tested were 5, 15, and 60 minutes and link-specific fixed tolls. Each scenario was run iteratively until the toll revenue and total delay hours stabilized and were consistent with one another (see Appendix B for details). Compared to the baseline scenario with no tolls, delay-based pricing (with time-varying tolls) reduced VMT by 2.5%, VHT by 13%, and total delay hours by 44%. The generated revenue was around $3.45 M, which averages to $1.17/resident per day or $0.42 per vehicle-trip (in year 2035). This is about 3 times what Texas' current gas tax would deliver (at $0.384/gal, or less than $0.02/mile, on average [Texas Comptroller, 2016]). Interestingly, the frequency at which the tolls are changed (every 5 minutes vs 15 minutes vs 1 hour) did not affect the aggregate results. Moreover, restricting to link-specific fixed tolls yielded similar benefits, as adding the time-varying aspect to the tolls only yielded 12% additional net delay reductions. This demonstrates that the ability to impose tolls at the link level accounts for the majority of the impact. This is encouraging, as it suggests that high temporal complexity is not a prerequisite for an effective congestion pricing strategy, thereby supporting the potential for simpler and more interpretable toll structures.

Figure 2 shows the average toll in the network weighted by link lane-miles during each 15-minute interval under delay-based pricing, topping out at approximately $0.05-0.06 during the AM and PM peaks. Discretization of time seems to matter in how the tolls are set, especially during peak periods. The AM peak tolls are $0.01 higher per mile on average when tolls are varied every 15 minutes vs every hour, while the opposite is true for the PM peak. The average toll when the tolls are not time-dependent is around $0.04 per mile. Figure 3 illustrates the spatial distribution of tolls during the AM and PM peak periods when toll-changing interval is 15 minutes. 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. The link-specific fixed tolls also the same spatial pattern. This can be used to inform geographic boundaries for other CP strategies, such as cordon tolling.

Figure 4 shows the differences in daily vehicular flow for each link in the network under delay-based pricing compared to the baseline scenario. Many links in the core area of Austin see significant decreases in flow of over 1000 vehicles per day. Links that see similar levels of increase are fewer, and there are no obvious spatial concentrations, except in some segments of the MoPac and IH35 expressways. This suggests that delay-based congestion pricing is successful in dispersing vehicular flow from highly congested links onto numerous other alternate routes.

Figure 5 illustrates the distribution of departure times and the % change from the baseline scenario, as well as the number of vehicles moving in the network for each minute of the simulation. 5-minute and 1-hour toll-changing interval scenarios are omitted from the figure, but they follow the same pattern as the 15-minute toll-changing interval scenario. While the differences in the distribution are subtle, there are significant shifts in trip start times in the evening as a result of delay-based pricing. Interestingly, the shift is towards the peak rather than having a peak-shaving effect, and the same effect is seen regardless of whether the tolls vary by time or remain fixed. Departures during the peak hours of 5-7 PM rose 6-8%, while departures 7 PM onwards fell by 8%. This is likely because the more travelers value the congestion reduction during the PM peak, which align closer to their preferred activity start times, than the tolls they pay. However, the number of vehicles on the road at once during the PM peak decreases (Figure 5, left), as congestion and travel times fall.

Changes in mode share due to delay-based pricing was negligible for the case of Austin. The share of person trips taking place in a private vehicle in the baseline scenario was 93% and did not decrease for any all delay-based pricing scenario. The vehicle occupancy did not increase either, only reducing the number of vehicle trips by less than 0.4% across all scenarios. 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 distances and times to key activities. Under delay-based pricing with tolls varying every 15 minutes, discretionary trips saw 3-6% reductions in the distance traveled, while travel distances to work trips remained unchanged. 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). Percentage reductions in average travel times are more than double those of average travel distances. Full-time work trips saw some of the largest travel time reductions at 11.7%, even though work trips had no change in travel distance, indicating a considerable decrease in network delays.

Table 1. Aggregate Summary of Results for Delay-Based Pricing Scenarios

Scenario	**VMT (miles per weekday)**	**VHT (hours per weekday)**	**Toll Revenue (in $/day)**	**Total Delay Hours**	**Average Speed (mph)**
Baseline	60.1 M mi/d	2.17 M hr/d	$0	503 K hr/d	27.7 mph
Delay-based (5 min avg)	58.5 M	1.89 M	$3.37 M	285 K	30.9
Delay-based (15 min avg)	58.5 M	1.89 M	$3.45 M	280 K	31.0
Delay-based (1 hr avg)	58.5 M	1.88 M	$3.47 M	280 K	31.0
Delay-based (fixed)	58.0 M	1.89 M	$3.74 M	304 K	30.6

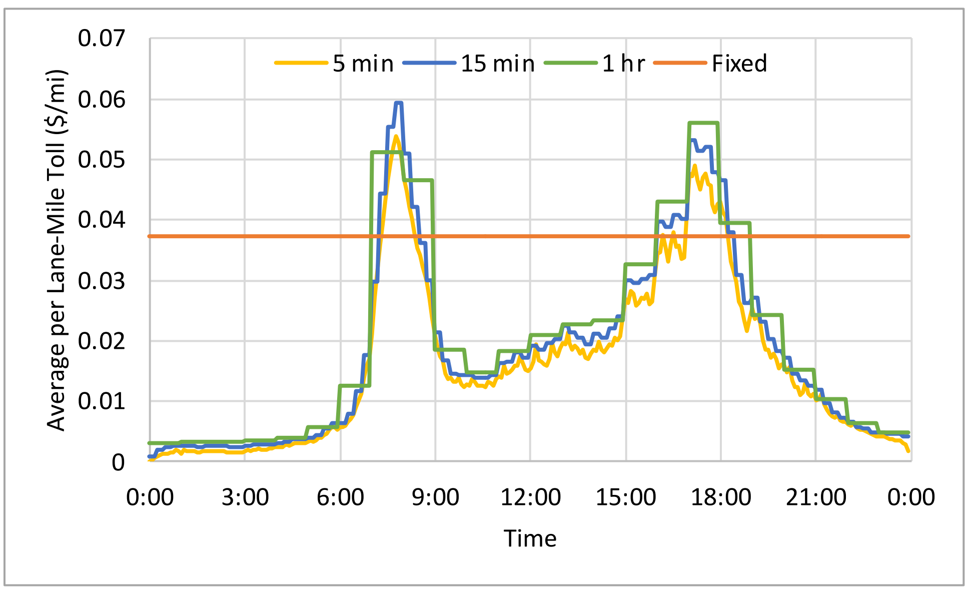

Figure 2. Average Toll being Charged (per Lane-Mile) under Delay-Based Pricing (assuming tolls updated every 5, 15, or 60 minutes, versus fixed/constant tolls)

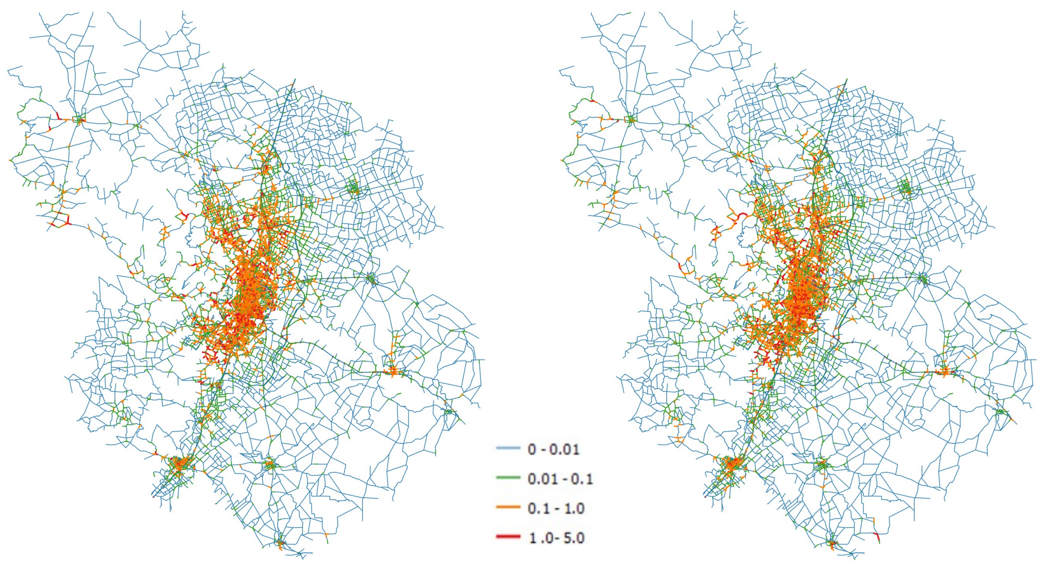

Figure 3. Delay-based Per-Mile Tolls during AM Peak (7:30 – 7:45 pm) and PM Peak (5:00-5:15 pm) across Austin's 2035 Network (with tolls updated every 15 minutes)

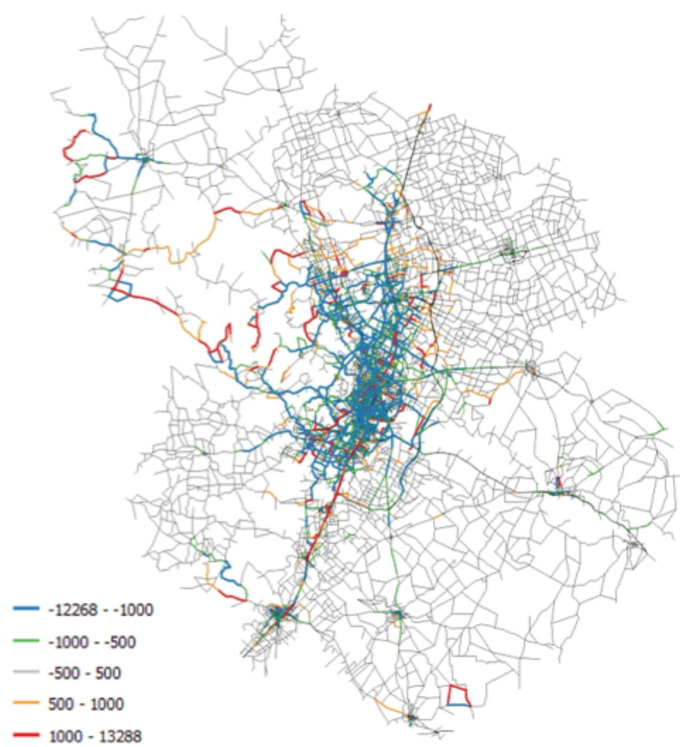

Figure 4. Differences in Daily Link Flows (vehicles/day) under Delay-Based Pricing (tolls updated every 15 minutes) compared to the Baseline.

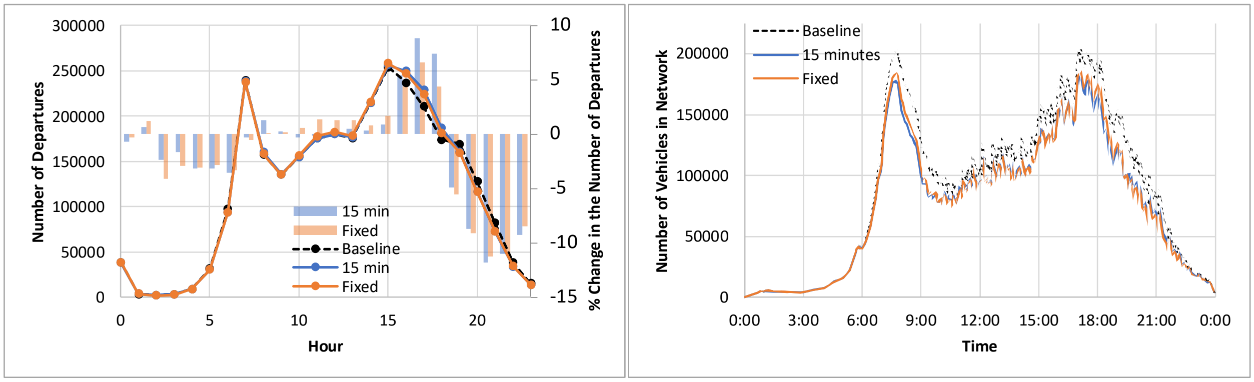

Figure 5. Person-trip Departures Each Hour and Percent Change from Baseline Scenario under Delay-Based Pricing (left) and Number of Vehicles Active/Moving in the Network by Time of Day (right)

Table 2. Changes in Average Travel Distances and Times to Activities under Delay-Based Pricing (tolls updated every 15 minutes)

	Baseline		Delay-Based (15 min)			
Activity	Average Travel Distance (mi)	Average Travel Time (min)	Average Travel Distance (mi)	% Change from Baseline	Average Travel Time (min)	% Change from Baseline
Work (full-time)	13.5 mi	20.6 min	13.4 mi	-0.7 %	18.2 min	-11.7%
Work (part-time)	13.9	20.2	13.8	-0.7	18.5	-8.5
Eating out	8.0	14.6	7.7	-3.9	13.1	-10.4
Personal	7.2	11.8	6.9	-4.5	10.7	-9.7
Religious/Civic	7.5	12.6	7.1	-5.4	11.2	-10.9
Service	7.1	11.6	6.7	-5.1	10.4	-10.1
Shopping (major)	7.9	13.0	7.4	-6.3	11.5	-11.9
Shopping (other)	7.0	12.2	6.6	-4.8	11.0	-10.1
Social	8.7	14.5	8.2	-5.4	12.7	-12.4

Distance-Based Pricing

Table 3 shows the overview of results for distance-based pricing scenarios. Tolls were iteratively set to generate the similar revenues to the delay-based pricing scenarios. The basic flat per-mile implementation resulted in \$0.06/mile. In addition, simple spatial and temporal variations were investigated. Although such variations might bring distance-based pricing closer to the complex-to-deploy delay-based pricing, it would be more costly to implement than a flat per-mile toll. The location-based adjustment involved using the large cordon (Figure 1) to distinguish per-mile tolls inside and outside the boundary. The ratio of the tolls was determined based on the delay-hours generated per VMT in each area under the baseline scenario, resulting in \$0.16/mile inside the cordon and \$0.05/mile outside. The TOD-based adjustment implemented different rates for 7 AM to 9 AM (AM peak), 9 AM to 3 PM (midday), and 3 PM to 7 PM (PM peak), and no tolls outside these hours. These intervals were determined based on the general shape of the curve showing the number of vehicles moving in the network. The ratio of the tolls was determined similarly to the location-based adjustment, based on the delay-hours generated per VMT in each TOD interval. This resulted in \$0.10/mile, \$0.04/mile, and \$0.09/mile for the AM peak, midday, and PM peak, respectively. Finally, applying both location and TOD adjustments resulted in the tolls shown in Table 4.

Compared to delay-based pricing (Table 1), a flat distance-based pricing policy collecting a similar amount of revenue led to a greater VMT reduction of 4.3%, but VHT and delay reduction were lesser at 5.5% and 11%, respectively. A simple location-based adjustment yielded additional 4% in total delay hours reduction. On the other hand, TOD-based adjustment with 3 time periods did not lead to any tangible improvements. Similarly, combining both types of adjustments did not produce outcomes better than location-based adjustment only. This result echoes that of delay-based pricing, in that the spatial variations of tolls are more important than temporal variations.

Figure 6 shows the differences in daily vehicular flow for each link in the network under distance-based pricing compared to the baseline scenario. The pattern differs from that of Figure 4, highlighting the different effects on network flow under delay- and distance-based pricing. Highway and major arterial links see notable decreases in flow of over 1000 vehicles per day, while other links, including very congested ones in the CBD, experience little change. Very few links see increases in vehicular flow, except for some links in the outer northwest region. However, links in the periphery are sparsely modeled, so a more detailed network is needed to precisely assess how traffic is diverted through these regions (Mori et al., 2024).

Table 5 shows the change in the average travel distances and times to key activities. The percentage reductions in average travel distances to discretionary activities were nearly double that of delay-based pricing (Table 2). However, average travel times also only fell by the approximately the same margin, and travel times to workplaces did not have significant reductions. This suggests that most of the VMT and VHT reductions under distance-based pricing likely come from travelers opting for closer destinations.

Table 3. Aggregate Summary of Results for Distance-Based Pricing Scenarios

Scenario	**VMT (miles per weekday)**	**VHT (hours per weekday)**	**Toll Revenue (in \$/day)**	**Total Delay Hours**	**Average Speed (mph)**
Baseline	60.1 M mi/d	2.17 M hr/d	\$0	503 K hr/d	27.7 mph
Distance-based (flat)	57.5 M	2.05 M	\$3.49 M	447 K	28.1
Distance-based (location adjusted)	57.3 M	2.02 M	\$3.49 M	428 K	28.4
Distance-based (TOD adjusted)	57.7 M	2.05 M	\$3.50 M	444 K	28.2
Distance-based (TOD + location adjusted)	57.9 M	2.04 M	\$3.49 M	430 K	28.5

Table 4. Per-Mile Tolls for Location- and TOD-Adjusted Distance-Based Pricing

	7 AM – 9 AM	**9 AM – 3 PM**	**3 PM- 7 PM**
Outside large cordon	\$0.09/mi	\$0.04/mi	\$0.07/mi
Inside large cordon	\$0.21/mi	\$0.12/mi	\$0.26/mi

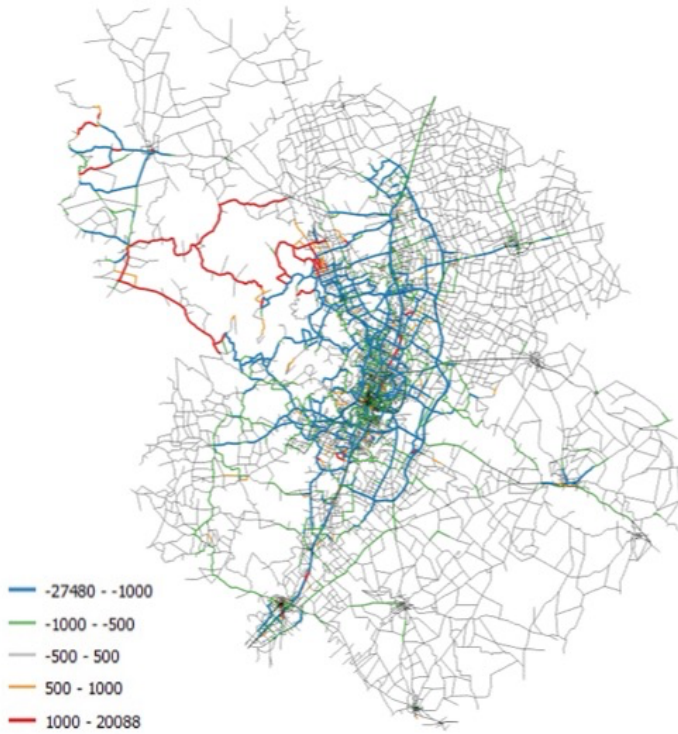

Figure 6. Daily Link Flow Differences (vehicles/day) under Distance-Based Pricing (flat per-mile) compared to the Baseline.

Table 5. Changes in Average Travel Distances and Times to Activities under Distance-Based Pricing (flat per-mile)

	Baseline		Distance-Based (flat)			
Activity	Average Travel Distance (mi)	Average Travel Time (min)	Average Travel Distance (mi)	% Change from Baseline	Average Travel Time (min)	% Change from Baseline
Work (full-time)	13.5 mi	20.6 min	13.3 mi	-1.4%	20.1 min	-2.5%
Work (part-time)	13.9	20.2	13.7	-1.3	19.7	-2.6
Eating out	8.0	14.6	7.4	-7.9	13.6	-6.9
Personal	7.2	11.8	6.6	-8.5	11.0	-7.5
Religious/Civic	7.5	12.6	6.7	-10.2	11.5	-8.9
Service	7.1	11.6	6.4	-9.6	10.6	-9.0
Shopping (major)	7.9	13.0	7.1	-10.3	11.9	-8.8

Shopping (other)	7.0	12.2	6.4	-8.7	11.3	-7.4
Social	8.7	14.5	7.9	-9.0	13.3	-8.2

Cordon Tolling

Under the baseline scenario, 3.5% and 7% of personal auto trips entered the small and large cordons, respectively. Therefore, the base target toll revenue of the cordon tolls was set to $124,000 and $248,000 per day, respectively. The number of entry points to the cordon are also roughly the same ratio. Therefore, the percentage of deployment and operation costs to be taken out of the revenue for the large cordon can be expected to be no more than that of the small cordon. The tolls when entering (not exiting) the Austin's core (Figure 1) between 7 AM and 6 PM is shown in Table 4, along with a summary of the results for the entire network. Table 5 shows the effect of cordon tolling on the links inside the cordons. Cordon tolling has little impact on the network-wide level when the toll is low or the cordon area is small. Greater benefits to network performance, including VMT, VHT, and delay reductions, are realized for both inside and outside the cordon as tolls are increased. Figure 7 shows the reductions in network delays, delays inside the cordon, and the number of vehicles entering the cordon as tolls are increased. Overall, the network delay reductions are greater with the large cordon, though the percentage reduction in delay inside the cordon is greater in the small cordon for similar toll levels. As tolls are increased, the network delay hours decrease almost linearly for both cordon sizes. This is also true for delay hours inside the large cordon, but diminishing returns can be observed for delay reductions inside the small cordon relative to the toll increase. However, the delay reductions are consistently greater than the vehicle entry reduction for the small cordon, while it is approximately 1:1 for the large cordon, though the reductions in vehicle entries follow a similar pattern for both cordon sizes. Cordon tolls are most effective in reducing congestion in areas with a high proportion of trips originating from outside the cordon, as trips that take place entirely within the cordon cannot be directly managed by the toll. However, larger cordons can create broader impacts by encompassing more congested areas within their boundaries. Therefore, an optimal cordon design should balance these factors, capturing enough area to maximize congestion reduction while maintaining a high proportion of trips originating from outside the cordon. Furthermore, it is possible to implement multiple cordons, although the deployment cost may be high.

Table 6. Aggregate Summary of Results for Cordon Toll Scenarios

Scenario	**Cordon Toll ($)**	**VMT (miles per weekday)**	**VHT (hours per weekday)**	**Toll Revenue (in $/day)**	**Total Delay Hours**	**Average Speed (mph)**
Baseline	$0	60.1 M mi/d	2.17 M hr/d	$0	503 K hr/d	27.7 mph
Small cordon	$0.56	60.0 M	2.16 M	$0.12 M	500 K	27.8
Small cordon (2x revenue)	$1.30	60.0 M	2.14 M	$0.25 M	479 K	28.0
Small cordon (5x revenue)	$4.18	59.9 M	2.12 M	$0.63 M	467 K	28.2
Small cordon (10x revenue)	$10.39	59.4 M	2.07 M	$1.25 M	436 K	28.7
Large cordon	$0.52	60.1 M	2.15 M	$0.25 M	485 K	28.0

Large cordon (2x revenue)	$1.15	59.8 M	2.14 M	$0.50 M	480 K	28.0
Large cordon (5x revenue)	$3.57	59.2 M	2.08 M	$1.24 M	442 K	28.5
Large cordon (10x revenue)	$8.31	59.0 M	2.03 M	$2.48 M	403 K	29.1

Table 7. Summary of Results for Links Inside the Cordons

Scenario	Number of Vehicles Entering Cordon	VMT Inside Cordon (miles per weekday)	VHT Inside Cordon (hours per weekday)	Total Delay Hours Inside Cordon	Average Speed Inside Cordon (mph)
Baseline (small cordon)	92,761	437 K mi/d	39.9 K hr/d	15.1 K hr/d	11.0 mph
Small cordon	76,384	409 K	35.8 K	12.5 K	11.4
Small cordon (2x revenue)	68,345	372 K	29.3 K	8.1 K	12.7
Small cordon (5x revenue)	57,073	327 K	24.3 K	5.7 K	13.5
Small cordon (10x revenue)	48,981	281 K	19.8 K	3.9 K	14.2
Baseline (large cordon)	181,634	3.02 M	189 K	73.2 K	16.0
Large cordon	159,695	2.94 M	180 K	67.5 K	16.3
Large cordon (2x revenue)	146,426	2.87 M	171 K	60.7 K	16.8
Large cordon (5x revenue)	125,006	2.71 M	154 K	50.5 K	17.6
Large cordon (10x revenue)	112,293	2.57 M	137 K	39.4 K	18.7

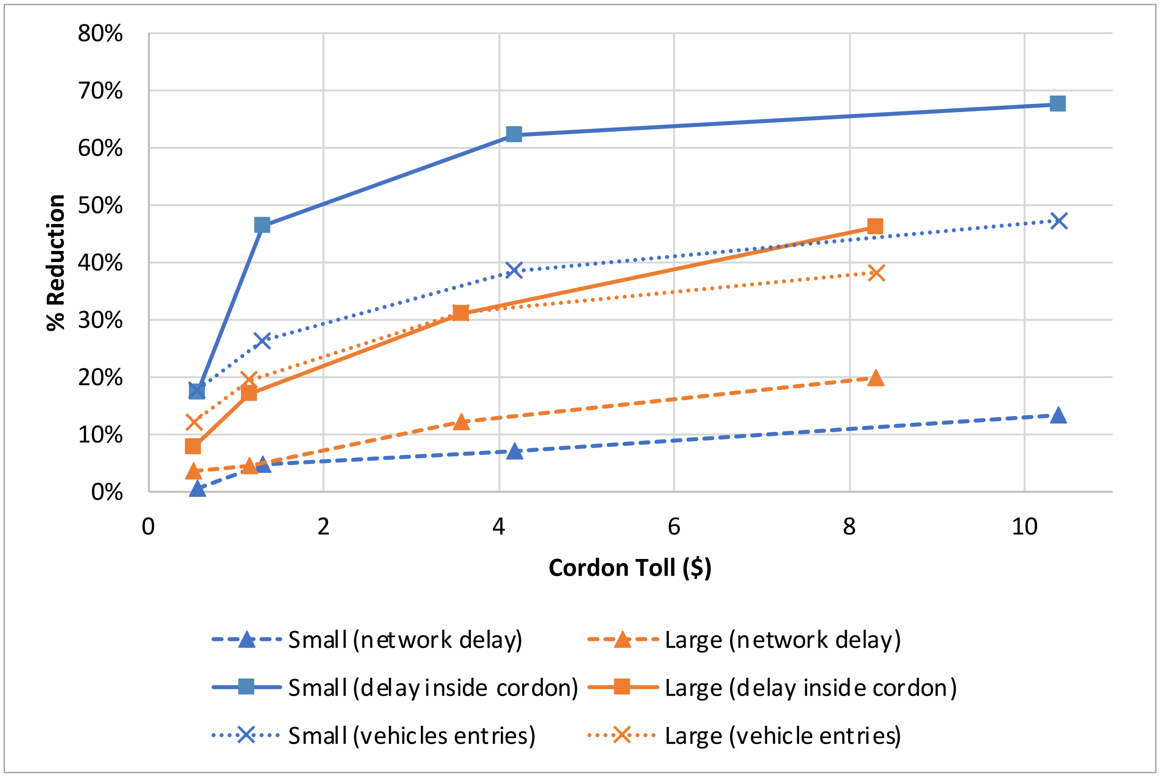

Figure 7. Delay Reductions Across the Whole Network, Delay Reductions Within the Cordon, and Reduction in Cordon Vehicle Entries at Different Tolling Levels (for small and large cordon designs)

Equity

In order to assess the equity implications of the CP strategies, the spatial disparities in the impacts were investigated. Figure 8 shows the average daily tolls paid per driving resident in each traffic analysis zone (TAZ) in the delay- and distance-based tolling scenarios. According to the simulation results, 66% of the region's projected 2.95 million residents for 2035 will drive on a given weekday. Even though the toll revenue does not change between the two scenarios, the spatial distributions of who pays the tolls 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 3) 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 9 shows the distribution of the tolls paid by driving residents per day under the two CP strategies. Under delay-based pricing, toll payments follow an exponential distribution, with 10% of drivers paying less than $0.10 per day. In contrast, distance-based pricing results in a lognormal distribution, where the highest concentration of drivers pays around $0.50, reflecting a typical distribution associated with travel distance. It should also be noted here that while the total toll revenue is comparable under the two scenarios, distance-based pricing relies more heavily on external and freight trips, with 26% of toll revenue generated from these trips compared to 19% under delay-based pricing. This has important implications for how tolls should be collected and reinvested.

Table 8 shows the impacts of the tolls by income class in terms of tolls paid and VMT and VHT reductions. For both delay- and distance-based pricing, the average toll/person/day varies little across income classes, which creates disproportionate financial burden for low-income earners. Therefore, subsidies or travel credits for low-income earners and its effects on their travel behavior must also be considered for these region-wide CP policies. However, no income class is (on average) adversely affected by either strategy, in terms of travel time or distance.

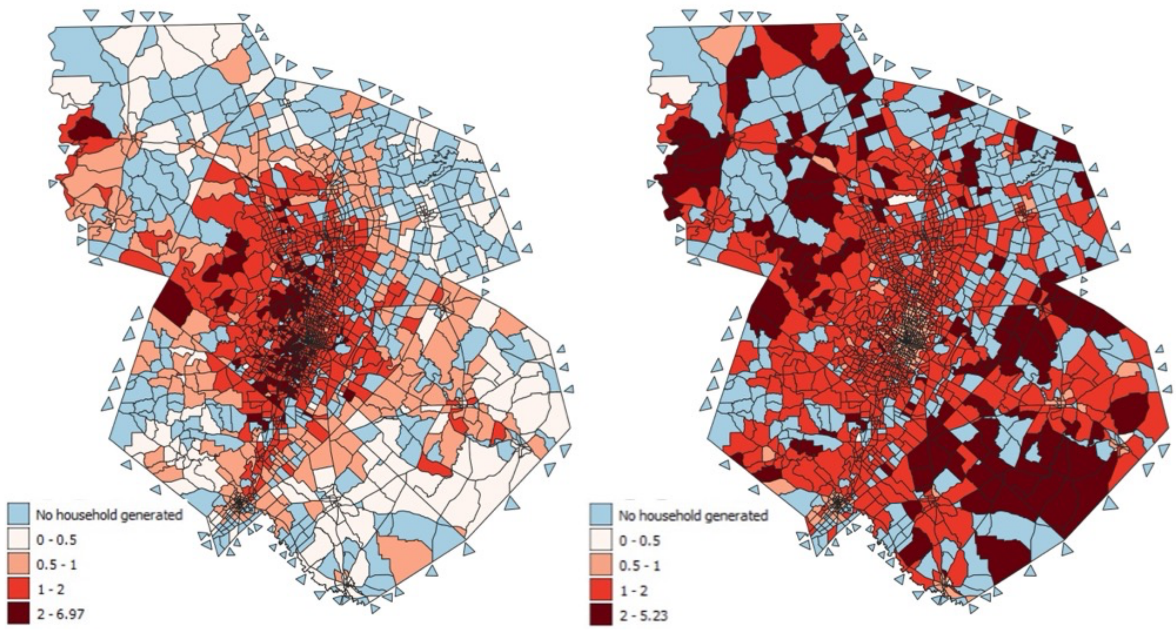

Figure 8. Average Daily Toll Paid per Driving Resident by TAZ under Delay- (left image, with tolls varied every 15 minutes) and Distance-Based (right image, with flat per-mile tolls) Tolling

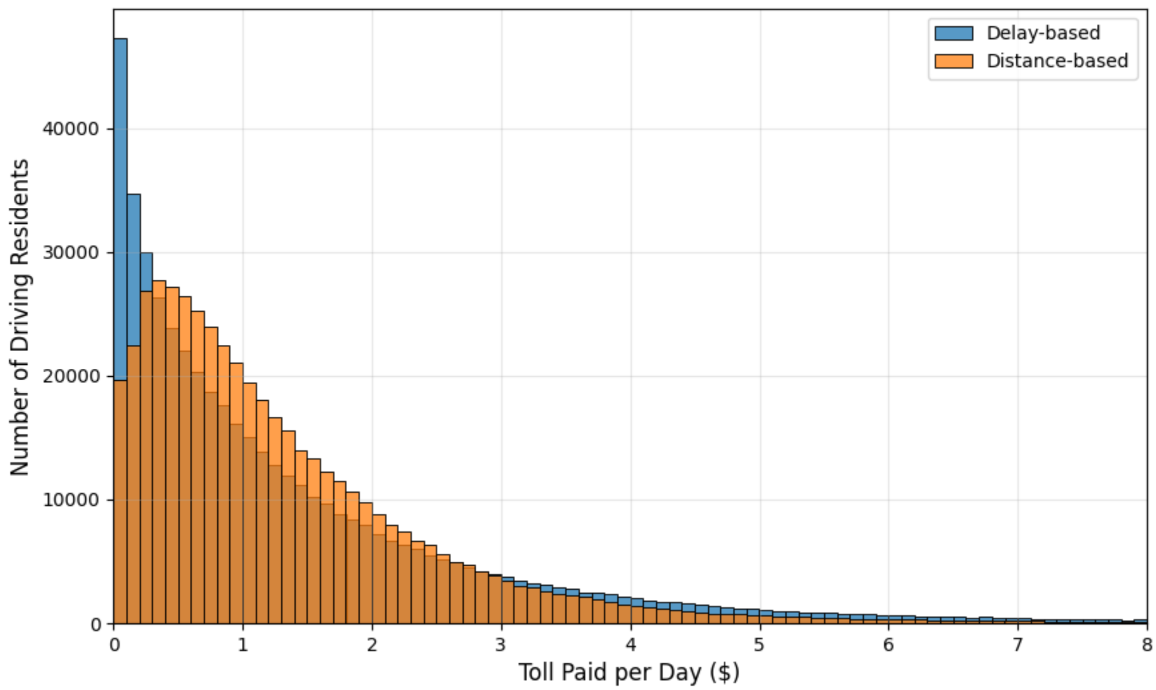

Figure 9. Distribution of Tolls Paid by Driving Residents per Day under Delay- (blue; tolls varied every 15 minutes) and Distance-Based (orange; flat per-mile) Pricing (bin width = $0.10)

Table 8. Tolling Impacts by Income Class

		Delay-Based Pricing			Distance-Based Pricing		
Income Class	**Annual Income**	**Avg. Toll/ Person/Day**	**% VMT Reduction**	**% VHT Reduction**	**Avg. Toll/ Person/Day**	**% VMT Reduction**	**% VHT Reduction**
Low	<$30,000	$1.30	4.6%	15.1%	$1.16	7.9%	8.3%
Lower-Middle	$30,000 - $60,000	$1.40	3.6%	13.8%	$1.27	6.0%	6.5%
Middle	$60,000 - $90,000	$1.42	3.4%	13.0%	$1.38	5.34%	6.0%
Upper-Middle	$60,000 - $150,000	$1.53	2.8%	13.0%	$1.40	4.7%	5.7%
Upper	>$150,000	$1.58	3.0%	12.9%	$1.43	4.4%	5.5%

CONCLUSIONS

This study applied variations of cordon, distance-based, and delay-based tolling strategies to Austin, Texas, using the POLARIS agent-based activity-based travel demand simulation model, examining 18 different scenarios. All CP strategies led to decreases in both network VMT and VHT but to different degrees. Delay-based pricing had the largest VHT reduction of 13% and reduced delays by 44%. The frequency of toll updates throughout the day had minor impact on the strategy's performance, meaning the ability to levy link-specific tolls is the key factor. This presents an opportunity for simpler and more interpretable toll structures, as it indicates that high temporal complexity is not a requirement for an effective CP strategy. Flat distance-based pricing, generating the same revenue as delay-based pricing, had the greatest reduction in VMT at 4% but lesser impacts on VHT and delay, which fell just 5.5% and 11%, respectively. While a simple location-based adjustment, which increased tolls in the core Austin area, led to improvements, a temporal adjustment based on four TOD periods did not. This result mirrors that of delay-based pricing, suggesting that the spatial variations of tolls play a more significant role than temporal variations. However, none of the distance-based pricing scenarios came close to rivaling the performance of delay-based pricing, indicating that developing an effective variation of distance-based pricing is a complex and non-trivial task. Cordon pricing had little impact, both inside the cordon and on the entire network, when generating a revenue proportional (in terms of trips affected) to the other two strategies, but higher tolls increase the effectiveness. While a larger cordon delivers greater network-wide benefits, a smaller cordon provides more focused improvements inside the cordon. Therefore, an optimal cordon design should capture enough area to maximize congestion reduction while maintaining a high share of trips coming in from outside the cordon.

Further effects of the CP policies were analyzed with regards to the choice dimensions of departure time, mode, destination, and route. Interestingly, the delay-based pricing strategy elicited travelers to shift towards the PM peak, rather than away from it, as travelers value the PM peak delay savings more than the tolls paid, since the PM peak aligns closer to 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 were to the reductions in travel distances, suggesting that VHT and delay reductions under distance-based pricing primarily stem from reductions in the distances driven. 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. Different patterns in route shifts were observed between delay- and distance-based pricing. While flows in the core area of Austin decreased under delay-based pricing, flow reductions were restricted to mostly highways and major arterials under distance-based pricing. 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, although this study successfully implemented heterogenous, driver-specific VOTT, the variations were limited to household income and trip purpose. Future studies should explore additional factors that may influence VOTT, such as the presence of other passengers in the vehicle and schedule constraints. Also, other externalities, such as emissions, should be included in tolls. Additionally, further investigations on equity and social welfare implications would be worthwhile. While systematic nested utilities are often used as measures of social welfare, POLARIS's activity-based model is a hybrid model combining random utility maximization with rule-based computational processes, meaning a comprehensive logsum value cannot be extracted from the model architecture (Zhao et al., 2012; Pinjari and Bhat, 2011). A welfare metric needs to be constructed for these types of models for a more thorough study on equity. Furthermore, future work should explore 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. Finally, the costs and practicality of deploying and administering CP strategies must be weighed against their potential benefits.

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APPENDIX A. VALUE OF TRAVEL TIME DISTRIBUTION

Figure 10 shows the distribution of the VOTT of road users weighted by travel time. The VOTTs are calculated as a function of trip type and household income from the POLARIS mode choice model, which was estimated from travel diaries collected by the Chicago Metropolitan Agency for Planning in 2016 and calibrated to Austin. The VOTTs and any dollar value results in this study are lower than what they would be in 2035, but they can be easily adjusted for inflation, and the findings of this paper hold without loss of generality. In addition to mode choice, agent-specific VOTTs affect activity-scheduling, destination choice, and routing decisions. The VOTT follows a bimodal distribution, representing work and non-work trips with average VOTTs of \$14.01/hour and \$11.49/hour, respectively. The overall average is \$12.40/hour, which is the value used to calculate delay-based tolls in this study. Freight activity is not explicitly modeled in this study but incorporated as exogenous trips. Their route choices are sensitive to tolling with a VOTT of \$60/hour (not included in Figure 10).

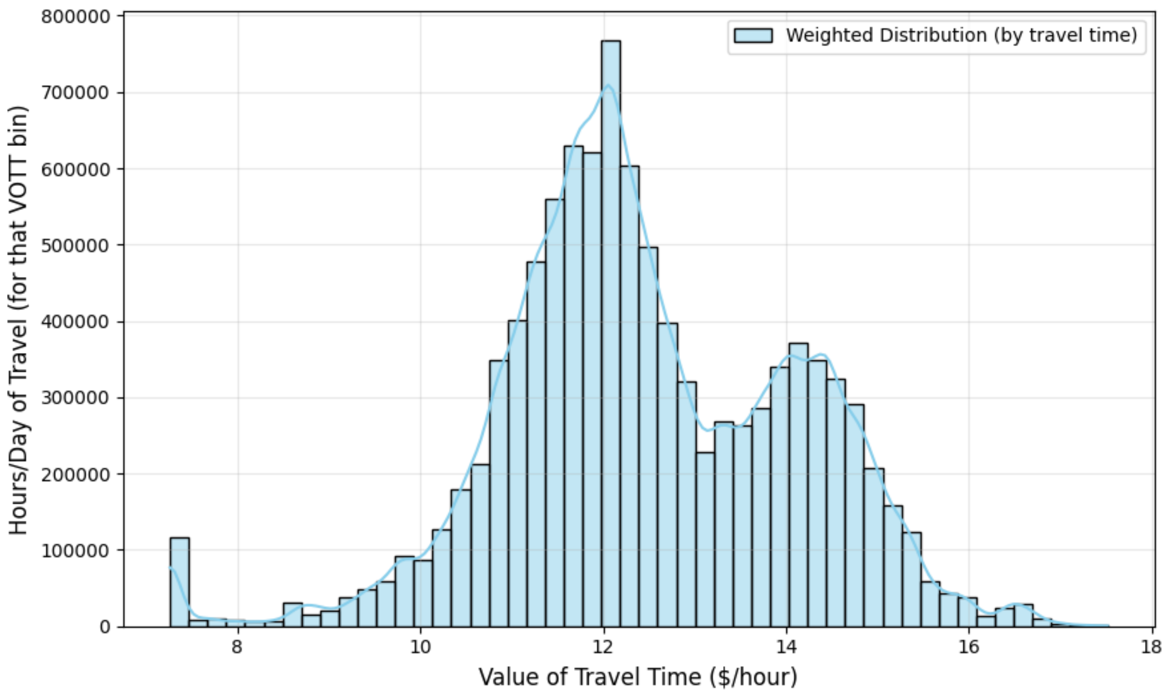


Figure 10. Distribution of Driver VOTT Weighted by Travel Time

APPENDIX B. CONVERGENCE OF DELAY-BASED TOLLS

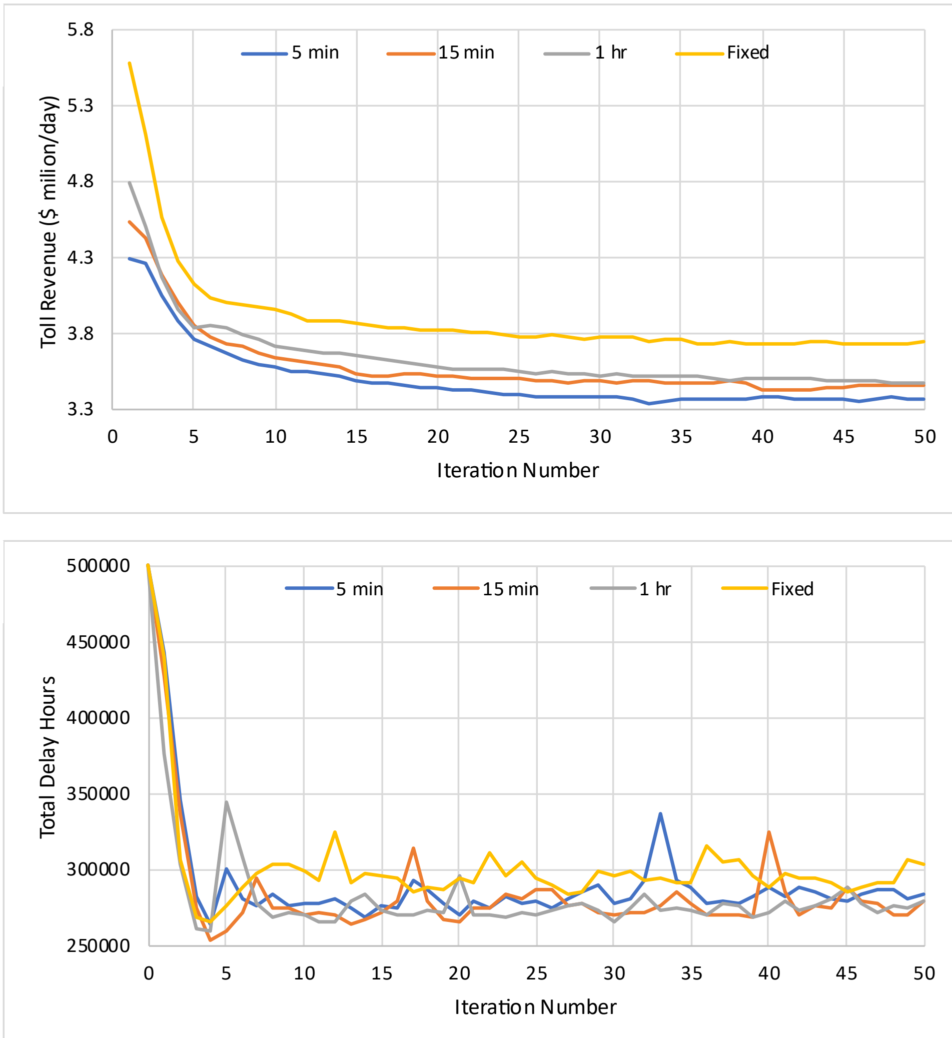
Figure 11 shows the changes in three metrics used to evaluate the convergence of delay-based tolls across 24-hour day simulations: toll revenue, total delay hours, and revenue gap, which is defined as:

$$revenue\ gap = \frac{(toll\ revenue)}{\bar{\beta}(total\ delay\ hours)} - 1 \tag{B1}$$

where $\bar{\beta}$ is the average VOTT. Positive values mean that road users are overcharged for the delay they are causing, while negative values are indicative of undercharging. In all delay-based pricing scenarios, the toll revenue decreased relatively smoothly, converging around the 30th iteration (Figure 11(a)). Total delay hours (Figure 11(b)) reached the vicinity of the final value more quickly in about 10 iterations but fluctuated from one iteration to another. The revenue gap (Figure 11(c)) was within ±10% after the 13th iteration with two exceptions. However, systematic overcharging of tolls can be observed for 5-minute, 15-minute, and 1-hour toll-changing interval scenarios until around the 35th iteration, after which the revenue gap seems stabilize around 0. On the other hand, the 5-minute toll-changing interval scenario consistently undercharges tolls after 23rd iteration and does not converge in the same way as the other scenarios. This may be because the 5-minute average delays are more variable from one iteration to another compared to longer averaging intervals. Better convergence may be obtained by running several iterations with the same tolls and using the average delays of those iterations to update the tolls. The results shown in Table 1 are from the 50th iteration.

(a)

(b)



(c)

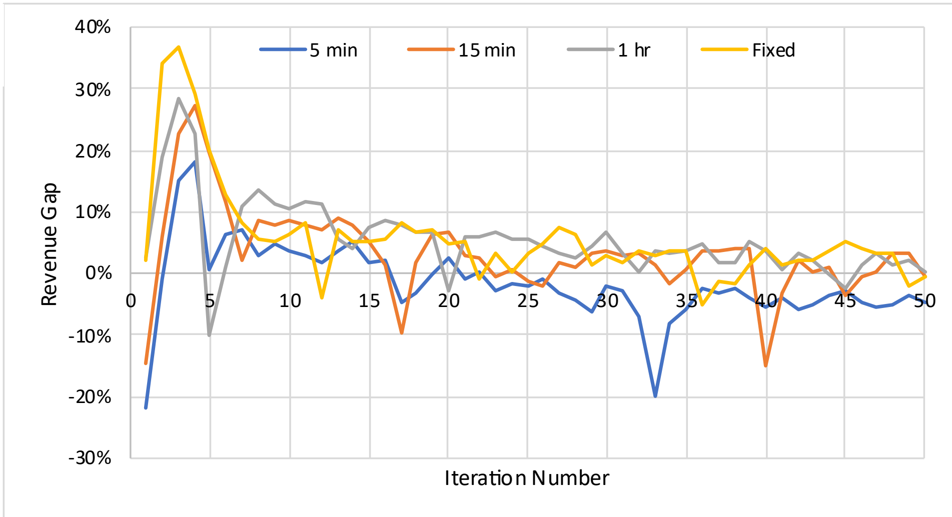


Figure 11. (a) Delay-Based Toll Revenue, (b) Total Delay Hours, and (c) Revenue Gap during Each Iteration for Each Toll-Changing Interval Tested

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