CONGESTION PRICING IN A WORLD OF SELF-DRIVING VEHICLES: AN ANALYSIS OF DIFFERENT STRATEGIES IN ALTERNATIVE FUTURE SCENARIOS

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ABSTRACT
The introduction of autonomous (self-driving) and shared autonomous vehicles (AVs and SAVs) will affect travel destinations and distances, mode choices, vehicle-miles traveled, and congestion. Although some congestion reduction may be achieved (thanks to fewer crashes and tighter headways, long-term), car-trip frequencies and VMT are likely to rise significantly in most settings, compromising the benefits of driverless vehicles. Congestion pricing (CP) and road tolls are key tools for moderating demand and incentivizing more socially and environmentally optimal travel choices. This work develops multiple CP and tolling scenarios and investigates their effects on Austin, Texas network conditions and traveler welfare, using the agent-based simulation model MATSim. Results suggest that, while all pricing strategies reduce congestion, their social welfare impacts differ in meaningful ways. More complex and advanced strategies may considerably improve traffic conditions, but do not necessarily improve traveler welfare. The possibility to refund users by reinvesting toll revenues as traveler budgets, plays a salient role in the overall efficiency of each CP strategy.

INTRODUCTION
Recent advances in autonomous vehicles (AVs) are generating much discussion across academia, industry, and news media. Considerable progress has been made in AV technologies, thanks to investments by technology companies and auto manufacturers (Muoio, 2017), along with support of public institutions (Kang, 2016). Since driverless passenger vehicles represent a new travel option, many passenger-trips made via existing, traditional modes, like cars, public transit, and bikes, will be replaced by trips in AVs and SAVs. While AV and SAV benefits may accrue in road safety and energy consumption (Fagnant and Kockelman, 2015), network congestion impacts are less well understood and may be quite problematic (Litman, 2017; Wadud et al., 2016).

On one hand, automated technologies can ultimately road network performance by reducing traffic crashes (and the delays those entail) and eventually increasing traffic throughput by ensuring tighter headways between vehicles and by making better use of intersections. However, AVs and SAVs will likely increase the number and the distance of motorized trips by making driving “easier” (by removing the driving burden) and car-travel more accessible (to persons with disabilities and those not owning cars, for example). Congestion may dramatically worsen, and demand management options will become even more valuable along congested corridors and in urban regions.
Charging drivers for the delays or congestion they cause (on those behind them, for example) is a well-known concept among economists, traffic engineers and transport professionals. Various congestion pricing policies now exist in cities like Singapore, London (UK), Stockholm (Sweden), Milan (Italy), Gothenburg (Sweden). Most are limited to rather simplistic cordon or area-based tolls that do not vary by congestion level. Smartphones and/or connected vehicles offer cities, states and nations an opportunity to implement more economically efficient and behaviorally effective strategies, thanks to advanced communication and location capabilities and fast information sharing.

This study investigates the effects of different congestion pricing strategies in future scenarios characterized by strong market penetration of AVs and SAVs. Schemes include a joint (time-plus-distance-based) charge that varies with the Austin region’s overall network condition, and a time-varying link-based charge that reflects marginal delay costs on following travelers at the link level. These schemes’ traffic and social welfare impacts are investigated and compared to those of two much simpler but rather classic strategies: a distance-based (flat) toll and a facility-based toll (for the most congested 2-4% links of the road network).

To reflect the technology’s uncertain development costs, capabilities and adoption rates, this work estimates two distinctive technology-adoptions scenarios: one with relatively high private AV reliance and the other with high SAV uptake.

Use of congestion pricing in AV and SAV scenarios is relatively unexplored, with the exception of a few theoretical studies (as described below). Here, scenario simulations use the multi-agent travel-choice model MATSim (www.matsim.org). MATSim enables simulation of tens of thousands of individuals and self-driving vehicles with flexibility in departure time, route, activity engagement and mode (and optionally destination).

The remainder of this paper offers the following: a brief discussion of AVs’ mobility impacts and their implications for congestion pricing, a description of the agent-based modeling framework used here, discussion of several future mobility scenarios and alternative congestion pricing strategies, analysis of the mobility and system welfare effects of such strategies, conclusions and policy recommendations.

MOBILITY IMPACTS OF SELF-DRIVING VEHICLES AND CONGESTION PRICING

Researchers interest on AVs’ impacts on travel behavior and traffic conditions is currently strong, with different studies now having investigated issues ranging from travel behavior studies to advanced traffic signal control applications. Milakis et al. (2017) provide a relatively comprehensive literature review, and the research community’s major findings are summarized below, followed by a discussion of congestion pricing.

Travel Costs and Traveler Preferences

AV travel costs will differ from those of conventional vehicles due to several factors. Fixed costs will be somewhat higher due to expensive hardware and software required (Litman, 2017). However, thanks to lower user effort and safer driving, travel time and operating costs fall. Parking costs can also be a key consideration for many travelers (Litman and Doherty, 2011), and “parking search” time can represent a significant portion of travel time in very busy settings (Shoup, 2006).

To date, there is little consensus in the scientific community about the impacts of AVs on travelers’ value of travel time (VOTT). While some argue that autonomous travel might not substantially affect travelers’ overall time-cost perceptions (Cyganski et al., 2015; Lenz et al., 2016; Yap et al., 2016), most assume and/or estimate (using stated-preference data) a lower VOTT (see, e.g., van den Berg and Verhoef, 2016; Lamotte et al., 2017; Zhao and Kockelman, 2017; Bansal and Kockelman, 2017).

SAV costs are likely to be under $1/mile, thanks to no driver wages (Fagnant and Kockelmann 2016; Loeb and Kockelman 2018; Chen et al. 2016; Bosch et al., 2017). Most of the previous literature on SAVs has focused on the effects of replacing trips and on the required fleet sizes for full the replacement of conventional trips (Burns et al., 2013; Spieser et al., 2014; Fagnant et al., 2015; Chen et al., 2016; Bischoff...
and Maciejewski, 2016). Only a few studies have focused on investigating their adoption from a travel demand modeling perspective (Krueger et al., 2016; Haboucha et al., 2017; Scheltes and Correia, 2017; Martinez and Viegas, 2017).

Changes of traffic conditions

Autonomous driving will affect traffic conditions in several ways. Thanks to reduced reaction times and shorter following distances, road and intersection capacity may eventually increase (Dresner and Stone, 2008), thereby reducing delays. Cooperative technologies like vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication can improve network performance (Tientrakool et al., 2011; Shladover et al., 2012; Hoogendoorn et al., 2014). Interestingly, Talebpour and Mahmassani (2016) use microsimulations to show how automation can play a larger role than connectivity in terms of capacity impacts. Most of these improvements will likely occur only for large adoption rates of self-driving and connected vehicles.

However, reduced driving burdens, lower travel cost, and improved transport access, will probably increase car use and travel distances in the near term, delivering more congested traffic conditions long before CAV technologies can resolve many capacity issues (Gucwa, 2014; Fagnant and Kockelman, 2015; Milakis et al., 2017). Empty SAVs driving in between trips will may compound this effect, with actual increases depending on each region’s policies, mode options, parking costs, and trip-making patterns, for example. For Berlin, Germany, SAVs (without dynamic ride-sharing among strangers) added 13% VMT (Bischoff and Maciejewski, 2016). Re-balancing vehicles during off-peak times may help to minimize the effect of those trips (Winter et al., 2017; Hörl et al., 2017). However, the possibility of pooling multiple travelers on SAVs with dynamic ride-sharing could reduce the overall VMT (Fagnant and Kockelman, 2018).

Congestion pricing for AVs

The idea of charging individual travelers for the marginal external congestion cost of their trips (associated with the delays’ caused to other users) has a long tradition in the transportation economics and engineering field (Pigou, 1924; Walters, 1961; Vickrey, 1963, 1969; Beckman, 1965). During the past fifty years, several studies have investigated the topic of congestion pricing to identify optimal strategies and to add more realistic features to their models based on travelers’ behavior and infrastructure performance (Small and Verhoef, 2007; de Palma and Lindsey, 2011). The adoption of AVs and the emergence of mixed-flow scenarios bring new theoretical and practical challenges for pricing.

From a theoretical perspective, AVs will affect the demand curve (volumes of road users). As discussed in Section 2.1, the possibility to perform other activities while driving and the different level of comfort, will likely affect AV users’ travel costs and perceived VOTT. As van den Berg and Verhoef (2016) highlight, a decrease of VOTT would correspond to a reduction in queuing costs for AV users, ultimately increasing their acceptance of increased travel time. Hence, from a marginal cost perspective, this phenomenon could hurt conventional users, whose travel costs have not changed.

In addition to that, AVs will affect the supply curve (response of the transportation system to the demand). As discussed in Section 2.2, AV implementation will likely yield improvements in network performance. Lamotte et al. (2016) considers some of these aspects by investigating the problem of optimal allocation of road infrastructure (between conventional and automated cars) and tolls with a bottleneck model. In case of shared road infrastructure, congestion phenomena becomes more complicated. From a traffic flow perspective, increasing levels of AVs would delay the onset of congestion (shift of Critical Density in the Fundamental Diagram1), allowing additional demand without compromising traffic conditions. However, larger portions of AVs will also accelerate the deterioration of traffic conditions in the congested traffic

1 The Fundamental Diagram relates a roadway’s traffic flow and density values (Lighthill and Whitman, 1956; Richards, 1956).
regime (increase of congested wave speed). Hence, from a marginal cost perspective, higher shares of AVs would be beneficial to all travelers up to a certain level of traffic demand (capacity).

From a practical standpoint, the high level of information and communication characterizing autonomous driving might favor the introduction of more advanced tolling strategies. Ideally, tolls should reflect changes in travel costs depending on category of road user, time of the day, real-time traffic conditions, trip purpose, and presence of transportation alternatives like public transit (Vickrey, 1997; Arnott, 1998). However, current road and congestion pricing strategies typically include: facility-based tolls (on bridges, tunnel, highways) specific roads, tunnels and bridges; cordon-based tolls (charge applied when entering an area, like in Stockholm); area-based tolls (charge applied when driving inside the area, like in London); and distance-based tolls (like in heavy goods vehicles charges in Germany).

In the past, research in the field has been characterized by a clear distinction between “first-best pricing” solutions, with strong analytical frameworks and the absence of constraints, and “second-best pricing” solutions, characterized by sub-optimal, but more feasible mechanisms (Verhoef, 2002; de Palma et al., 2004; Zhang and Yang, 2004; May et al., 2008; Lawphongpanich and Yin, 2010).

The possibility of exchanging traffic and charges information in real-time to all the connected vehicles would allow for more advanced pricing strategies that vary in time, space and fare more dynamically. In this sense, AV technologies could almost bring second-best pricing systems to first-best pricing ones. Driverless technologies can also facilitate congestion pricing in other ways. First, tolling systems could become more feasible thanks to advanced communication technologies (wireless, GPS), cheaper than the current tolling systems based on dedicated short-range communications (DSRC) and automated license plate recognition since they do not need for additional road infrastructure. Second, the fact that “smart” AVs can compute and communicate fares and routing options to travelers would help keeping pricing schemes understandable and transparent. This might eventually increase public acceptability of congestion pricing (Gu et al., 2018).

In Section 5.2, we present two congestion pricing schemes that leverage on the advanced communication and computation capabilities of AV-SAVs to derive schemes closer to the concept of first-best pricing. To the best of our knowledge, congestion pricing schemes involving both privately owned AVs and SAVs are still relatively unexplored except for a few studies in specific simulation environments (agents’ route choice under dynamic link tolls) (Sharon et al., 2017) or involving broader external costs for some specific modes (limited to SAVs and conventional cars) (Kaddoura et al., 2018). In this study, we provide a comprehensive analysis of different potential future scenarios (accounting for different market penetrations of AVs and SAVs) and alternative congestion pricing schemes.

**MODELING AVs AND SAVs WITH AN AGENT-BASED MODEL**

In this section after providing a brief overview of the agent-based model MATSim, we present a description of our modeling framework. We then focus on the modeling of AVs and SAVs.

**General Framework of MATSim**

MATSim simulates an entire daily plan of every single user and it considers endogenous mode choice, departure time choice and route choice into a fully dynamic model. As opposed to models that use single trips, this model allows for predictions on reactions to demand management strategies, such as tolls during the span of a day, accounting for a higher level of realism. In fact, trips are typically linked to each other as a part of a daily plan and not that meaningful just as stand-alone trips (Balmer et al., 2006). Activities often have higher importance in the daily schedule than trips that simply represent connections among them. Since MATSim represents traffic behavior at a highly disaggregated level by modeling individual agents (with different socio-demographic characteristics), it is possible to investigate the effects of transport
policies on travel behavior and traffic more in depth than in traditional 4-steps models (Kickhöfer et al., 2011). The overall process (Figure 1) can be summarized in the following stages:

- Each agent independently develops a plan that expresses his/her preferences in terms of activities, trips and their schedules during the day (Initial demand).
- The agents simultaneously perform all the plans in the mobility simulation’s (Mobsim’s) physical system. Congestion phenomena are modeled using a queue model, which takes both the physical storage capacity and the actual throughput (flow capacity) of a link into account.
- To compare different plans’ performances, each scored using a utility-type function (Scoring).
- Agents are able to remember their plans and improve them during the simulation by means of a learning algorithm (Replanning). During the implementation the system iterates between plan generation and traffic flow simulation.
- The cycle continues until the system has reached an equilibrium where no agent can improve anymore his score (Analyses).

Figure 1: MATSim cycle (source: Horni et al., 2016)

The choice model generally adopted in MATSim is equivalent to the standard multinomial logit model. Since the amount of plans in the memory of agents is limited, the worst performing one is replaced by a new one at each iteration. Thanks to this feedback mechanism agents are able to improve their plans over several iterations until the system reaches the “relaxed” state when agents cannot significantly improve their plans and the outcome of the system becomes stable. This state is also referred as agent-based stochastic user equilibrium (Nagel and Flotterod, 2009).

For further information about the simulation framework MATSim, see Horni et al. (2016).

Choice dimensions and parameters

Plans can be improved by changing the time of departure, varying the route and choosing different transport mode through modules. Agents’ travel choices are modeled in MATSim through an iterative learning mechanism based on a quantitative score, referred to as utility. For each iteration agents choose from an existing set of daily plans according to a multinomial logit model.

Every daily plan is associated with a utility, accounting for a trip-related disutility and a performing activity utility:

\[ V_{plan} = \sum_{i=1}^{n} (V_{act,i} + V_{trip,i}) \]  

where \( V_{plan} \) is the total utility of a daily plan; \( n \) is the total number of activities or trips; \( V_{act,i} \) is the utility for performing activity \( i \); and \( V_{trip,i} \) is the utility of the trip to activity \( i \). The first and the last activity are wrapped around the day, and handled as one activity. Thus, the number of activities and trips is the same. The trip-related utility for a each mode is calculated as follows:

\[ V_{q,i} = \beta_{0,q} + \beta_{t,q} \cdot t_{i,q} + \beta_{c} \cdot c_{i,q} \]
where $\beta_{0,q}$ corresponds to the alternative specific constant of mode $q$; $t_{i,q}$ corresponds to the travel time of leg $i$ traveled with mode $q$; $\beta_{t,q}$ corresponds to the marginal utility of traveling by mode $q$; $c_{i,q}$ corresponds to the monetary cost of leg $i$ traveled by mode $q$; and $\beta_c$ corresponds to the marginal utility of monetary cost.

To calculate the positive utility gained by performing an activity, a logarithmic form is applied (Charypar and Nagel, 2005; Kickhofer et al., 2011):

$$V_{\text{act},i}(t_{\text{act},i}) = \beta_{\text{act}} \cdot t_i^* \cdot \ln\left(\frac{t_{\text{act},i}}{t_{0,i}}\right) \quad (3)$$

where $t_{\text{act}}$ is the actual duration of performing an activity (when the activity is open), $t_i^*$ is an activity’s ‘typical’ duration, and $\beta_{\text{act}}$ is the marginal utility of performing an activity at its typical duration. In the equilibrium, all activities at their typical duration are required to have the same marginal utility; therefore, $\beta_{\text{act}}$ applies to all activities. $t_{0,i}$ is a scaling parameter linked to an activity’s priority and minimum duration.

In this study, $t_{0,i}$ is not relevant, since activities cannot be dropped from daily plans.

The value of travel time saving (VTTS) is derived as follows:

$$\text{VTTS} = \frac{\beta_{\text{act}} - \beta_{t,q}}{\beta_m} \quad (4)$$

where $\beta_m$ corresponds to the marginal utility of money.

The travel options modeled in this study include: car, public transit, bike and walked (modeled jointly), AV, and SAV. The behavioral parameters for car and public transit used in this study are based on Tirachini et al. 2014 and Kaddoura et al. 2015 and have been adjusted to reflect more realistically current travel costs in the US (2017). The parameters used for the simulation are summarized in Table 1. In order to account for aspects such as parking and walking times of car users we have derived an alternative specific constant $\beta_{0,\text{car}} = -0.1$. In addition to that, car users pay a monetary cost proportional to the distance traveled corresponding to $0.20$-$0.30$ per mile, depending on the scenario. Since, waiting, egress and access times are not modeled in these experiments, public transit (PT) has been recalibrated yielding an alternative specific constant $\beta_{0,\text{PT}} = -1.5$. This value also accounts for the average ticket cost and for the particular reluctance of American society in using public transit. In similar fashion, the alternative specific constant for walking/biking has been set to $\beta_{0,\text{active}} = -0.2$. Similar to Kaddoura et al. (2015), the marginal utility of traveling by car is set to zero. Even if this value is set to zero, traveling by car will be implicitly punished by the opportunity cost of time (Horni et al., 2016). In this study, the marginal utility of money $\beta_m$ is equal to 0.79 such that the VTTS for car users corresponds to about $18$ per hour. This value has been obtained according to the recommendations from the US DOT (2011).

The parameters for AVs have been mainly derived based on (Kockelman et al., 2017). The monetary costs are estimated to be around $0.20$ per mile. The purchasing costs might be higher than conventional cars, but the higher initial investment would be compensated by the increased efficiency and better insurance premiums. We assume AVs to have a null alternative specific constant in order to account for parking and walking time reductions. The marginal disutility of traveling equal to +0.48 to reflect a marginal cost of traveling equal to 50% of those of car users (corresponding to a VTTS of about $9$ per hour), in line with Gucwa (2014) and Kim et al. (2015)².

As for SAVs, we assume the same alternative specific constant and marginal cost of traveling of AVs. Unlike AVs, SAVs are characterized by waiting times depending on the availability of vehicles. We assume

² Note that, in MATSim, setting a positive marginal disutility of traveling does not imply a gain of score from the trip since agents are
the monetary costs to be composed of a flat fee, a distance fare that change depending on the scenario (see the following sections for further details).

Table 1: Mode choice parameters used

<table>
<thead>
<tr>
<th>Travel Mode</th>
<th>$\beta_0$</th>
<th>$\beta_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car</td>
<td>-0.1</td>
<td>0</td>
</tr>
<tr>
<td>Public Transit</td>
<td>-1.5</td>
<td>-0.36</td>
</tr>
<tr>
<td>Walk/Bike</td>
<td>-0.2</td>
<td>0</td>
</tr>
<tr>
<td>AV</td>
<td>0</td>
<td>+0.48</td>
</tr>
<tr>
<td>SAV</td>
<td>0</td>
<td>+0.48</td>
</tr>
</tbody>
</table>

In addition to travel choices, agents can modify their activities’ scheduling decisions by shifting, extending or shortening activities considering aspects like the optimal duration, and opening/closing times of the facility (Table 2). Activities performed outside opening times do not yield any positive gain of utility. Furthermore, agents are subject to schedule penalty costs for being early or late accordingly to well-known Vickrey’s parameters: $\alpha$, $\beta$, and $\gamma$ (Arnott et al., 1990).

Table 2: Travelers’ out-of-home activity attributes

<table>
<thead>
<tr>
<th>Activity Type</th>
<th>Optimal duration</th>
<th>Opening time</th>
<th>Closing time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>14</td>
<td>undefined</td>
<td>undefined</td>
</tr>
<tr>
<td>Education</td>
<td>5</td>
<td>08:00</td>
<td>22:00</td>
</tr>
<tr>
<td>Work</td>
<td>7</td>
<td>07:00</td>
<td>undefined</td>
</tr>
<tr>
<td>Shopping</td>
<td>1</td>
<td>09:00</td>
<td>01:00</td>
</tr>
<tr>
<td>Leisure</td>
<td>2</td>
<td>09:00</td>
<td>01:00</td>
</tr>
</tbody>
</table>

Simulation of Shared mobility services and road capacity increase

The simulation of SAVs is performed by means of an extension of MATSim that allows for a dynamic vehicle routing problem (DVRP) (Maciejewski et al., 2017). The DVRP contribution reproduces dynamically demand responsive modes such as conventional taxis and ride hailing services. As opposed to the standard vehicle routing in MATSim, which is conducted before each iteration starts, the DVRP module allows an online dispatch of vehicle fleets. Vehicle dispatch is generally started the moment an agent wishes to depart using such a mode.

For the simulation of large fleets of SAVs, a straightforward, rule-based dispatch algorithm is used, that has been applied in previous case studies with more than 100,000 vehicles (Bischoff and Maciejewski, 2016). The algorithm aims at reducing the required number of vehicles during peak hours and thus minimizes the required fleet to serve all the received requests. This issue is addressed by a “demand-supply balancing” vehicle dispatch strategy, in which the system is classified into two mutually-excluding categories, namely oversupply, with at least one idle SAV and no open requests, and undersupply, with no idle SAVs and at least one open request. Both states are being handled in different ways. In the first case, when a new request is placed, the nearest vehicle is dispatched towards it. In the latter case, when a vehicle
becomes idle it is dispatched to the nearest open request. In times of oversupply, requests are served immediately, whereas in times of undersupply, a vehicle will first be dispatched to requests waiting in close proximity and thus may leave requests waiting for a longer time. This helps to maximize the throughput of the system. Despite its simplicity, this strategy provides solutions which are close to those of more complex methods, such as solving iteratively the taxi assignment problem (Maciejewski et al. 2016).

In order to account for the capacity increase resulting from reduced reaction times and shorter following distances, a specific MATSim module is adopted that allows for traffic simulation of mixed autonomous/conventional flows (Maciejewski and Bischoff, 2017). This is achieved by lowering the capacity (maximum flow) required by AVs to travel on a link by a factor of 1.5. This means that a link which may otherwise be passed by a maximum of 1000 conventional vehicles per hour could be passed by 1500 AVs per hour. If a mixed flow of AVs and conventional vehicles are passing the link, the maximum flow lies between these values, depending on the actual vehicles’ mix (Figure 2). The results of the model are in line with those in Levin and Boyles (2016), who proposed a multiclass cell transmission model for shared human and AV roads.

Figure 2: Impact of AVs on traffic flow

SIMULATION SCENARIOS

The impacts of different pricing schemes are investigated for three different scenarios. The first one, which is referred to in this work as the “Base Scenario” corresponds to a realistic simulation of the city of Austin and surroundings (Figure 3), comprising a considerable portion of the Austin metropolitan area (Greater Austin). The studied region includes a series of satellite cities such as Round Rock, Cedar Park, and Pflugerville. The road network used in the simulation consists of a high-resolution navigation network including about 211,000 road segments (links). The population and its plans have been obtained by adjusting those from Liu et al. (2017) who used CAMPO’s household data for Austin 2020. Although the plans have not been formally validated, resulting trip distances and durations are reasonably realistic. Normally, each agent needs to travel at least once per day to execute his plans. Instead of simulating the full population, a sample of 5% (equivalent to 45,000 agents) is used for the experiments of this study. Link capacities are downsized to match these with the sample size. The available transportation modes are car,
public transit and walk/bike (modeled jointly). In order to reflect current trends in availability of car as a travel option, we assume 90 percent of agents to have access to car (either as a driver or passenger).

Figure 3: Simulation Network (source: Google Maps)

The two additional scenarios correspond to possible future scenarios characterized by the presence of AVs and SAVs. Currently, it is not clear whether AVs will mainly replace privately owned vehicles or if they are going to be adopted as shared taxis. On one hand, the auto industry is moving quickly to provide the first “partially autonomous” models (Level 3) by 2020 and full autonomous models by 2030 (Level 4 and Level 5) (Kockelman et al., 2017). Conversely, ride-sharing companies (Uber, Lyft, Didi) are already running tests (Kang, 2016; Hawkins, 2017), making considerable investments (Buhr, 2017), and developing important partnerships (Russell, 2017) to put driverless fleets on the road within a few years. Hence, an “AV-oriented” Scenario and a “SAV-oriented” Scenario are included representing these two opposite trends. In the AV-oriented scenario, it is assumed that a large portion of the population will switch from car to AV (90% of agents having accessibility to car in the Base Scenario). In this scenario, the cost of AVs is equal to the car cost ($0.20 per mile). SAVs are available too, but the fleet size is relatively small (one vehicle every 30 agents) and they are characterized by lower prices than the current shared mobility services ($0.5 flat charge, 0.4 $/mile distance charge and 0.1 $/min time charge). For example, a trip of 5 miles, from the northern suburbs to downtown, would vary approximately between $3.70 and $5.20 depending on traffic conditions. In the SAV-oriented scenario, SAVs are largely available (one vehicle every 10 agents), whereas most of the population is still car-dependent (only 10% has access to privately owned AVs whose costs is increased to $0.30 per mile). Furthermore, we assume a decrease of availability of privately owned vehicles to 60% in order to reflect a decrease of ownership (Litman, 2014). In this scenario, SAVs are characterized by lower prices than in the AV-oriented scenario (a 50% reduction), assuming that main ride-sharing companies and local authorities would stipulate agreements on prices concerning the provision of shared autonomous services. In this case, the same type of trip described above would cost approximately between $1.80 and $2.60 (slightly higher than a public transit pass).

Results of MATSim simulations in terms of modal shift are reported in Figure 4. In the Base Scenario, a car clearly appears as the dominant travel option, in line with the current situation. In the AV-Oriented Scenario and SAV-Oriented Scenario, the introduction of two additional travel options (SAVs and AVs)
generate significant changes. PT trips decrease in the AV-Oriented Scenario (to 5% of the mode share), whereas they increase SAV-Oriented Scenario (to 15% of the mode share). This result is partly due to the lower ownership of private vehicles, which forces a considerable portion of commuters to travel with either PT or SAVs. “Active trips” decrease to 4% and 7% respectively in the AV-Oriented Scenario and SAV-Oriented Scenario. As a result of this shift, congestion measured as daily total vehicle-miles traveled (VMT) and daily total travel delay increase in both the scenarios (Table 3). The increased capacity due to autonomous driving is offset by the increased trips particularly in the SAV-oriented Scenario by the empty SAV trips that account for 6.6% of the total VMT.

**Figure 4: Modal Share for the three different scenarios**

**Table 3: Traffic conditions of the three different scenarios**

<table>
<thead>
<tr>
<th></th>
<th>Base Scenario</th>
<th>AV-oriented Scenario</th>
<th>SAV-oriented Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Daily VMT</td>
<td>2,845,406</td>
<td>3,106,669</td>
<td>3,032,629</td>
</tr>
<tr>
<td>VMT by Empty SAVs</td>
<td>2,845,406</td>
<td>4,741</td>
<td>201,828</td>
</tr>
<tr>
<td>Total Travel Delay</td>
<td>437,887</td>
<td>459,781</td>
<td>523,594</td>
</tr>
<tr>
<td>(veh-hours per weekday)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**CONGESTION PRICING SCHEMES**

In this study, we investigate the performance of four different congestion pricing schemes. A facility-based and distance-based scheme are considered “traditional schemes” (Section 5.1), as they are well known in the academia and real world. A link-based marginal cost pricing scheme and a joint distance-time scheme are considered “advanced schemes” (Section 5.2) because they are more complex and they require cutting-edge technologies (such as those of connected-automated vehicle) for implementation.

**Traditional congestion pricing strategies**

Facility-based tolls are probably the most common form of congestion pricing since they do not require particularly advanced technologies for implementation. In the past, this type of scheme has been implemented mainly on tunnels, bridges and highway facilities that represent major bottlenecks. In this study, a “Link-based Scheme” is applied to the one thousand most congested links during the morning peak hours (7-9AM) and evening peak hours (5-7 PM). The tolled links are selected based on the
volume/capacity (V/C) ratio calculated on hourly basis and aggregated for the peak hour periods. A minimum threshold V/C ratio of 0.9 is chosen to identify the most congested links, resulting in the selection of about 2-4% of the road network (3,911 links in the Base Scenario, 5,100 links in the AV-Oriented Scenario, and 3,820 links in the SAV-Oriented Scenario). As it possible to see in Figure 4, the tolled links include the most important segments of road infrastructure of the region such as Interstate 35 and the Texas State Highway Loop 1. A flat toll rate of $0.20 is set to all the selected links regardless of the amount of congestion and the characteristics of the link.

Here, the **Distance-based Scheme** toll varies simply with distance traveled, at a rate of $0.20 per mile traveled by motorized vehicle between 7AM and 8PM. One could make it more time or location dependent, requiring on board GPS to keep track of their position (and tally the owed charges before reporting back to a fixed roadside or gas-pump-side device, for example). Of course, many nations, states and regions are interested in distance-based tolls or VMT fees, especially when more fuel-efficient and electric vehicles pay relatively few gas taxes. Clements and Kockelman (2018) discuss such tolling options, and the strengths and weaknesses of various tolling technologies.

![Figure 5: selected links in the Link-based Scheme for the Base Scenario (source VIA:Senozon)](image)

**Advanced congestion pricing strategies**

The first advanced congestion pricing strategy investigated consists of a dynamic Marginal Cost Pricing (MCP) scheme at link level. MCP in the context of road usage, consists in charging users for the extra cost (shadow cost) that their trip cause to other users (Walters, 1961) due to congestion. According to MCP models, an optimal static link-based toll $\tau$ can be derived for each link such that:

$$\tau = V \cdot \frac{\partial c}{\partial V}$$  \hspace{1cm} (5)
Where $V$ corresponds to the traffic volume on the link and $c$ corresponds to the congestion costs that can be related to $V$ by means of several functions. However, MCP presents some theoretical and practical limitations, such as the necessity of dynamic features and difficulty of setting optimal link tolls for large networks (De Palma and Lindsey, 2011).

Communication and automation technologies installed in AV/SAVs offer the opportunity to apply different tolls on each link of a network such that vary dynamically according to traffic conditions. In the “MCP-based scheme” proposed, the cost of congestion on each link is derived by means of the Fundamental Diagram (FD), that expresses a relation between traffic throughput $q$ (veh/h) and density $k$ (veh/km) (Greenshields, 1935). According to the FD, the traffic throughput increases with density until reaching the critical density corresponding to the link’s capacity. For values of density above the critical ones, the throughput and (average) speed on the link decreases until zero.

Based on this concept, it is possible to derive for each link, its average speed $u(k, q)$ as function of density and outflow, as follows:

$$u(k, q) = \frac{q}{k}$$

(6)

Then, for each link, the total delay accumulated during the time interval $[t, t + \Delta t]$ corresponds:

$$d = \left[\left(\frac{l}{u_{t+\Delta t}} - \frac{l}{u_t}\right) \cdot n\right]$$

(7)

where the first term corresponds to the marginal delay per time interval, which is given by the difference of travel time on link of length $l$ at the average speed $u$ and at free-flow speed $v$. The second term $n$ corresponds to the additional or fewer number of link users over the time interval $\Delta t$, that can be expressed as:

$$n = (k_{t+\Delta t} - k_t) \cdot l$$

(8)

Hence, the marginal cost pricing charge for each link $i$, during the time interval $[t, t + \Delta t]$ can be derived as:

$$\tau_i = \frac{d_i \cdot VTTS}{n_i}$$

(9)

where VTTS corresponds to the average value of travel time. For reasons of understandability and acceptability, each link’s charge varies over intervals of 15 minutes and it is derived by aggregating traffic condition measurements across 5 minute intervals. The fare has a maximum threshold value of $1. For practical reasons, given the size of the network, only a subset of 15,020 central links shown in Figure 6 is analyzed.
Figure 6: analyzed links in the MCP Scheme (source VIA:Senozon)

The second advanced congestion pricing scheme consists of a joint “Distance-Time-based scheme.” The main rationale behind this approach lies in the fact that traditional distance-based schemes do not really capture traffic dynamics. In certain cases, they can even become detrimental as drivers might be incentivized to take shorter (but more congested) routes (Liu et al., 2014). Including a toll component that charges users for time traveled, depending on the traffic conditions of the network could obviate this problem. In a similar fashion to the surge pricing mechanism, where prices are dynamically inflated based on demand, in the Distance-Time-based scheme the fare is identified as follows:

$$\tau = \varphi(l) + \sigma_{[t,t+\Delta t]}(t)$$ (10)

where $\varphi(l)$ corresponds to the distance dependent component and $\sigma_{[t,t+\Delta t]}(t)$ corresponds to the travel time dependent component for any given time interval $[t, t + \Delta t]$. The distance component is set to $0.10$ per mile between 7AM and 8PM, which is half of the Distance-based scheme charge. The component $\sigma_{[t,t+\Delta t]}(t)$ varies each hour, based on traffic conditions across all twelve 5-min intervals in that hour. In order to reflect changes of overall marginal cost of congestion on the network, the travel-time-dependent component is derived as follows:

$$\sigma_{[t,t+\Delta t]} = \frac{\sum_{i=1}^{N} d_i \cdot VTTS}{S \cdot r}$$ (11)

where links’ delay $d_i$ is calculated using Eq. 7, $S$ corresponds to the total number of departures over the time period $[t, t + \Delta t]$, and $r$ corresponds to the average trip duration on the network, which is derived as follows:
\[
  r = \frac{L}{U}
\]  \hspace{1cm} (12)

where \( L \) and \( U \) correspond respectively to the average trip length and average free-flow speed over the network.

Since both advanced schemes are intended to be consistent with traffic dynamics, which in turn depend on agents’ mode, departure time and route choices, we adopt a simulation-based feedback iterative process to derive the final toll values \( \bar{\tau} \). The approach utilizes as stopping criterion the overall change of network delay \( \Delta D \), which is the sum of all links’ delays. For each iteration \( j \), the algorithm performs the following steps:

- Identify toll values \( \bar{\tau}_j \) for each time interval \([t, t + \Delta t]\) by means of Eq. 9 or Eq. 10.
- Perform a MATSIM simulation until new stochastic user equilibrium is reached.
- Derive total network delay by aggregating links measurement: \( D = \sum_i^N d_i \)
- Check the change of total delay \( \Delta D \) between the current iteration \( j \) and the previous \((j-1)\). If \( \Delta D \) is less than 5%, stop. Otherwise, return to step 1.

The resulting fares for the MCP-scheme for the AV-Oriented and SAV-Oriented Scenario are determined after 10 to 15 iterations. Among the 15,020 links analyzed, between 2,000 and 3,000 are tolled (across the various 15-min intervals), with an average fare of $0.92.

Figure 7 illustrates fares for the Distance-Time-based scheme for both the AV-Oriented and SAV-Oriented Scenarios. The two schemes show similar trends in the variation of the travel time charge component during the peak hours, with higher fares during the evening peak. As expected, since the SAV-Oriented Scenario is characterized by higher delays than in the AV-Oriented Scenario, the levels of charge are higher.

---

3 We indicate with \( \bar{\tau} \) the vector of tolls for all the links considered.
RESULTS AND IMPLICATIONS

The impacts derived from the different congestion pricing schemes in each scenario are discussed in this section. The evaluation of the schemes is carried out by means of a set of commonly used performance indicators such as mode shift, change of traffic delay and motorized trips. The analyses continue with a comparison of system welfare effects, followed by a discussion about the policy implications of the different schemes.

Mode choice

All the schemes succeed in reducing car, AV and SAV trips to a different extent. In all the scenarios PT and slow modes, witness a considerable increase of mode share (Table 4-7).

Overall, the demand for SAVs and AVs seem more elastic than the demand for standard vehicles given the higher modal shift achieved for all the CP strategies. Because of their higher initial costs, AV and SAV travelers are more incentivized than car travelers to adopt PT or slow modes in presence of tolls. For this reason, CP strategies seem to be more effective in AV-oriented and SAV-oriented scenarios.

Among the traditional schemes, the Distance-based scheme generates larger changes in travelers’ mode choice than the link-based scheme in the Base Scenario. These results are in line with previous studies about distance-based schemes (Litman, 1999). Instead, in the scenarios characterized by large presence of AVs and SAVs the modal shifts are comparable. This is an interesting outcome, since the two schemes are conceptually very different from each other and might have different effects in terms of economic gains, distributional effects and public acceptability.

The MCP-based scheme determines travel behavior changes comparable to the ones achieved with the traditional Link-based scheme, although the total number of tolled links (and the area involved), and the levels of charge are lower.
The Distance-Time based scheme achieves the highest reduction of private trips in both scenarios. Compared to the “traditional” distance-based toll, including a travel time-based component in the fare allows for further reduction of car, AV and SAV trips, despite its lower distance-based component.

Table 4: Modal shift from the link-based scheme

<table>
<thead>
<tr>
<th></th>
<th>AV oriented</th>
<th>SAV oriented</th>
<th>Base (no SAVs-AVs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change of car trips (%)</td>
<td>-0.8</td>
<td>-7.92</td>
<td>-6.81</td>
</tr>
<tr>
<td>Change of PT trips (%)</td>
<td>28.07</td>
<td>16.20</td>
<td>5.89</td>
</tr>
<tr>
<td>Change of walk/bike trips (%)</td>
<td>10.73</td>
<td>7.50</td>
<td>0.91</td>
</tr>
<tr>
<td>Change of AV trips (%)</td>
<td>-37.94</td>
<td>-2.30</td>
<td>0.00</td>
</tr>
<tr>
<td>Change of SAV trips (%)</td>
<td>-0.05</td>
<td>-13.48</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 5: Modal shift from the distance-based scheme

<table>
<thead>
<tr>
<th></th>
<th>AV oriented</th>
<th>SAV oriented</th>
<th>Base (no SAVs-AVs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change of car trips (%)</td>
<td>-3.97</td>
<td>-7.31</td>
<td>-14.10</td>
</tr>
<tr>
<td>Change of PT trips (%)</td>
<td>35.55</td>
<td>14.74</td>
<td>2.89</td>
</tr>
<tr>
<td>Change of walk/bike trips (%)</td>
<td>11.11</td>
<td>5.74</td>
<td>11.29</td>
</tr>
<tr>
<td>Change of AV trips (%)</td>
<td>-42.62</td>
<td>-1.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Change of SAV trips (%)</td>
<td>-0.06</td>
<td>-12.10</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 6: Modal shift from the MCP-based scheme

<table>
<thead>
<tr>
<th></th>
<th>AV oriented</th>
<th>SAV oriented</th>
<th>Base (no SAVs-AVs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change of car trips (%)</td>
<td>-0.6</td>
<td>-9.62</td>
<td>-</td>
</tr>
<tr>
<td>Change of PT trips (%)</td>
<td>26.36</td>
<td>16.26</td>
<td>-</td>
</tr>
<tr>
<td>Change of walk/bike trips (%)</td>
<td>11.45</td>
<td>9.11</td>
<td>-</td>
</tr>
<tr>
<td>Change of AV trips (%)</td>
<td>-37.09</td>
<td>-2.63</td>
<td>-</td>
</tr>
<tr>
<td>Change of SAV trips (%)</td>
<td>-0.16</td>
<td>-13.12</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 7: Modal shift from the Distance-Time based scheme

<table>
<thead>
<tr>
<th></th>
<th>AV oriented</th>
<th>SAV oriented</th>
<th>Base (no SAVs-AVs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change of car trips (%)</td>
<td>-5.74</td>
<td>-33.1</td>
<td>-</td>
</tr>
<tr>
<td>Change of PT trips (%)</td>
<td>38.96</td>
<td>40.26</td>
<td>-</td>
</tr>
<tr>
<td>Change of walk/bike trips (%)</td>
<td>16.03</td>
<td>17.30</td>
<td>-</td>
</tr>
<tr>
<td>Change of AV trips (%)</td>
<td>-49.06</td>
<td>-3.99</td>
<td>-</td>
</tr>
<tr>
<td>Change of SAV trips (%)</td>
<td>-0.18</td>
<td>-20.00</td>
<td>-</td>
</tr>
</tbody>
</table>
Traffic performance of the network

Both traditional and advanced CP strategies determine a significant reduction of private trips traveled by AVs, SAVs and cars (Figure 8). Schemes with a distance dependent fee component do not necessarily achieve the highest reduction of VMT. For example, the link-based and MCP scheme, determine higher VMT reductions than the traditional distance-based scheme in both the AV-Oriented and the SAV-Oriented scenario. In general, the traditional schemes seem to yield much higher improvements in the AV-Oriented and SAV-Oriented scenario than in the Base Scenario because of higher elasticity of autonomous travelers. The MCP-based scheme produces a VMT reduction comparable or higher that achieved with the link-based scheme. The Distance-Time based scheme determines the largest decrease of travel demand in both the AV-Oriented and the SAV-Oriented scenario.

However, this is just a single perspective to evaluate the effects of the strategies, as the changes in terms of network daily travel delay show (Figure 9). Interestingly, in the AV-Oriented scenario all the CP strategies generate a considerable reduction of delays (above 50%). The results vary significantly according to the scheme. For example, the advanced CP strategies outperform the traditional schemes. In the SAV-Oriented scenario, all the schemes determine similar reductions of delays (around 25-30%), except for the Distance-Time based scheme. Despite changes in the mode shift of the traditional schemes in the Base Scenario are below 10%, the decrease of delay is above 30%. In this case, users seem to be more willing to reroute and reschedule their trips rather than switching to public transit.

Figure 8: Reduction of motorized trips for the different scenarios according to the congestion pricing scheme
Welfare changes

Maximization of social welfare is an important criterion to evaluate transportation policy decisions. The social welfare change due to the introduction of pricing policies can be estimated by means of the well-known “rule of the half”, which is given by the contribution of the gains/losses of existing users and gains/losses of new users. The main drawbacks of this approach include the possibility of considering different impacts of tolls on travel (changes in travel time and schedules) and users’ heterogeneity (Arnott et al., 1990).

Multi-agent simulations like MATSim partly overcome these issues by allowing a “non-conventional” economic appraisal based on the agents’ utilities as an economic performance indicator of the system. Although income differences across the population by means of the agents’ utility score are not considered in this study, it is possible to account for the main effects of congestion pricing schemes such as changes in travel costs and travel behavior, and revenues.

In this study, change of total welfare $\Delta \omega$ between the original scenario (with no toll) and any congestion pricing scenario is calculated as the sum of public revenues (first term in Eq. 13) and consumer surplus (second term in Eq. 13):

$$\Delta \omega = \tau + \sum_{j} \beta_{m} \cdot (V_{j} - V'_{j})$$

where $\tau$ is the sum of the collected toll revenues (in presence of tolls), $\beta_{m}$ is the negative marginal utility of monetary cost, and $V_{j}$ and $V'_{j}$ correspond to the total daily utility score for agent $j$ in the original scenario and in the congestion pricing scenario, respectively.

Table 8 summarizes the social welfare impacts of the different schemes for each scenario. The most effective strategy in terms of total welfare gains seems to be the Distance-based scheme in all scenarios (assuming that the toll revenues could be fully reinvested). The Link-based scheme determines an improvement of social welfare to a minor extent (between 2% and 4%, depending on the scenario).
Interestingly, the advanced CP strategies do not seem to yield improvements compared to the traditional ones. The high levels of congestion of the autonomous scenarios, and the lower attractiveness of PT and active modes as compared to autonomous transport, yield to relatively high tolls in those CP schemes that explicitly depend on traffic delays. The MCP scheme, compared to the link-based one, is penalized by the more limited area of action, particularly given the mobility configuration of Austin where traffic congestion is rather spread out over the network, and not just limited to the city center.

When the revenues are not considered, all of the CP strategies achieve a reduction in social welfare. In this case, the highest performance is achieved by the MCP-based scheme that determines the lowest reduction of consumer surplus in both the AV-Oriented and SAV-Oriented scenario. This is an important aspect to consider, since the ability to reinvest and the fraction of expendable revenues would determine whether a scheme is favorable.

Finally, the Distance-based, the Link-based, and the Time-Distance scheme perform similarly regardless of the level of private and shared AVs, whereas the MCP-based scheme behaves differently according to the scenario. In the SAV-Oriented scenario, the social welfare changes are higher than in the AV-Oriented scenario (about 0% and -10%, respectively).

<table>
<thead>
<tr>
<th>Table 8: Welfare changes for alternative CP schemes for each scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original Scenario-total welfare (Million $/day)</strong></td>
</tr>
<tr>
<td>-------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>Distance-Based Scheme: consumer surplus change</strong></td>
</tr>
<tr>
<td><strong>Distance-Based Scheme: welfare change with revenues</strong></td>
</tr>
<tr>
<td><strong>Total welfare change (%)</strong></td>
</tr>
<tr>
<td><strong>Link-Based Scheme: consumer surplus change</strong></td>
</tr>
<tr>
<td><strong>Link-Based Scheme: welfare change with revenues</strong></td>
</tr>
<tr>
<td><strong>Total welfare change (%)</strong></td>
</tr>
<tr>
<td><strong>MCP-Based Scheme: consumer surplus change</strong></td>
</tr>
<tr>
<td><strong>MCP-Based Scheme: welfare change with revenues</strong></td>
</tr>
<tr>
<td><strong>Total welfare change (%)</strong></td>
</tr>
<tr>
<td>Distance-Time Based Scheme: consumer surplus change ($ per capita per day)</td>
</tr>
<tr>
<td>------------------------------------------------</td>
</tr>
<tr>
<td>Distance-Time Based Scheme: welfare change with revenues ($ per capita per day)</td>
</tr>
<tr>
<td>Total welfare change (%)</td>
</tr>
</tbody>
</table>

**Policy implications**

All the investigated CP schemes are efficient in the sense that they decrease traffic demand and make the traffic flows more efficient by reducing traffic congestion.

From an economic perspective, some of the schemes do not yield to an overall increase of social welfare, whereas others might be progressive depending on the compensation schemes. However, benefits from reduced emissions, noise and road damage were not considered in the analyses.

The portion of revenues collected from the tolls that can be reinvested in the social welfare is crucial for the success and equity implications of the scheme. In the theory of congestion pricing, investments into public transit service are considered a progressive solution, especially for zones with public transport access (Ecola and Light, 2010). Other options could be by means of per-capita credits or income-based discounts.

Under these circumstances, it becomes particularly important to properly quantify the investment and maintenance costs for different schemes. For example, the employment of cheaper satellite and cellular technologies (compared to traditional tolling infrastructure) could lower the investment costs for advanced CP schemes and make them more attractive.

**CONCLUSION**

AVs and shared AVs will affect people’s mobility and traffic. It is not clear whether the benefits of more efficient traffic flows would compensate for the costs of increased trips and distance traveled. Congestion pricing schemes represent an opportunity to internalize the negative costs of traffic congestion. The novel transportation landscape, characterized by higher automation and connectivity, could facilitate the implementation of traditional and more advanced strategies.

In this study, we adopt an agent-based model to investigate the potential mobility, traffic and economic effects of different congestion pricing schemes in alternative future scenarios for the metropolitan area of Austin. From a traffic perspective, all the mobility schemes yield to considerable reductions of congestion. While advanced CP schemes are more effective than traditional ones in affecting travel demand and traffic, they do not bring economic gains. In all the scenarios, the Distance-based and Link-based schemes yield social welfare improvements.

The analysis of mobility scenarios by means of an agent-based model like MATSim allows a high level of realism since it is possible to explicitly model several factors concerning transportation demand and traffic. In the specific context of AVs-SAVs, the coexistence of different autonomous modes and cars is considered (in addition to public transit and walk/bike), as well as: the impacts of autonomous driving on increased capacity; the changes in travel costs and preferences, and the demand responsive mechanism of SAV services (with the phenomenon of empty trips). In future studies of AV-SAV scenarios, it would be interesting to include the effects of automation on destination choice and parking.

In the specific field of travel demand management, additional studies can be performed to investigate the distributional effects of different CP schemes (considering income heterogeneity across the population) and possible compensation measures.
ACKNOWLEDGEMENTS

The authors thank Michal Maciejewski and Amit Agarwal for fruitful discussions on the MATSim simulation, and Felipe Dias for support in the analyses. The study was partly funded by the Texas Department of Transportation under Project 0-6838, “Bringing Smart Transport to Texas”.
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