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 choice, and congestion. This work develops multiple CP and tolling strategies in alternative future scenarios, and investigates their effects on the 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.

INTRODUCTION

This study investigates the effects of different congestion pricing strategies in future scenarios characterized by strong market penetration of AVs and SAVs. Strategies include a travel time-based charge that varies with the Austin, Texas region's overall network condition and a time-varying link-based tollthat reflects marginal delay-costs at the link level. The traffic and social welfare impacts of these policies are investigated and compared to those of two much simpler but rather classic strategies: a distance-based toll and a flat facility-based toll (for the most congested 2 to 4% links of the network links). To reflect the technology's uncertain development costs, capabilities and adoption rates, this work estimates two distinctive technology-adoption 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). This paper's 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. In this specific study, travelers' behavioral responses to CP strategies include changes in departure times, routes, activity engagements and modes, while destinations are considered fixed. Although MATSim allows for detailed analyses of a wide range of road transportation externalities (such as emissions, noise and road damage), this study focuses on congestion costs.

MODELING AVs AND SAVs WITH AN AGENT-BASED MODEL

MATSim simulates the daily plan-set of all agents and considers endogenous mode choice, departure time choice and route choice, making it a fully dynamic model. 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 in more detail than in traditional 4-steps models (Kickhöfer et al., 2011). The overall process is shown in Figure 1

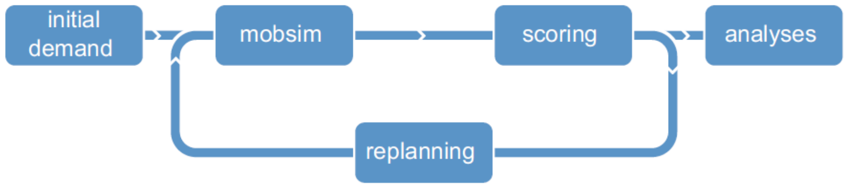

FIGURE 1 MATSim cycle (source: Horni et al., 2016)

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

In this study, daily itineraries or agents' plans contain up to five different activity types: "Home", "Education", "Work", "Shopping", and "Leisure", which can be linked via several possible trip-chain combinations As shown in Figure 2, each plans describes a tentative schedule of activities (with their locations) and travels to reach them. 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.


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FIGURE 2 Example of two agents' plans

The travel options modeled in this study include: car, public transit, bike and walk (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 the current travel costs in the U.S. (2017). The parameters used for the simulation are summarized in Table 1. Since the simulation approach does not explicitly account for parking costs and walking times of car users, we have derived an alternative specific constant $\beta_{0,car} = -0.1$. In addition, car users pay a monetary cost proportional to the distance traveled corresponding to \$0.30 per mile. Since, waiting, egress and access times are not modeled in these experiments, public transit (PT) has been recalibrated, yielding an alternative specific constant $\beta_{0,PT} = -1.5$. This value also accounts for the average ticket cost and for Americans' and Austinites' reluctance in using public transit. In a similar fashion, the alternative specific constant for walking/biking has been set to $\beta_{0,active} = -0.2$. 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 β_c 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 USDOT (2011).

The AV parameters have been largely derived from Kockelman et al.'s (2017) and Bosch et al.'s (2017) work. A \$0.20 per mile. A privately owned and operated AV is assumed to cost \$0.20 per mile since fuel economy, insurance costs, and maintenance costs should be lower than those of a conventional car (Bosch et al., 2017). 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 is set 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)[1].

As for SAVs, we assume the same alternative specific constant and marginal cost of traveling of AVs since they used by only one individual or party at a time. Unlike AVs, SAVs are characterized by waiting times depending on the availability of vehicles. We assume the monetary costs to be composed of a fixed flat fee, and variable distance fare and time fare, depending on the scenario (see the following sections for further details).

In addition to travel choices, agents can modify the start time and duration of each activity in their plan-set to reflect aspects like the optimal/target duration for the activity type, and site opening and closing times. Activities performed outside open/feasible times do not offer any added utility. Furthermore, agents are subject to schedule penalty costs for being early or late according to Vickrey's parameters: *α, β,* and *γ* (Arnott et al., 1990). Although agents' decision to drop activities is not explicitly modeled, when transportation costs are very high, agents' could extend their activities and render participation in following activities impossible.

The simulation of SAVs is performed by means of an extension to MATSim that allows for dynamic vehicle routing using the DVRP module (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 SAVs. Vehicle dispatch is generally started the moment an agent wishes to depart using such a mode (and SAVs cannot be booked in advance here). 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. In case of mixed flows of AVs and conventional vehicles on the link, the maximum flow lies between these values, depending on the actual vehicles' mix and following a flow capacity increase ratio of: $1/(1-s+s\cdot c)$, where s and c represent the share of AVs and the capacity increase parameter (equal to 0.666), respectively. Hence, the benefits of increased levels of AVs traffic are not linear. 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.

[1] Note that, in MATSim, setting a positive marginal disutility of traveling does not imply a gain of score from the trip since agents are

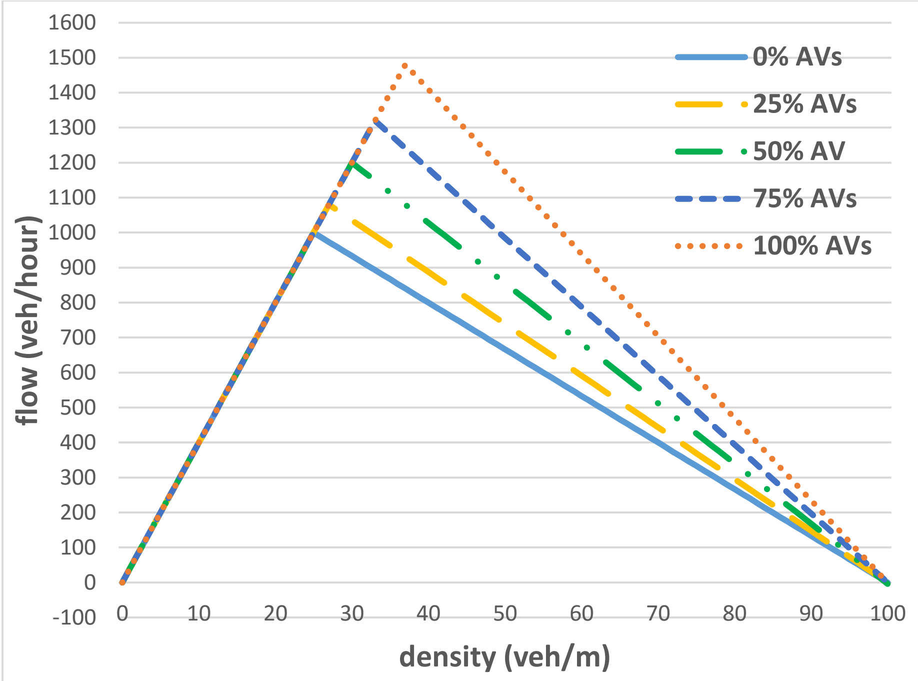

FIGURE 3 Impact of different shares of AVs on traffic flow

SIMULATION SCENARIOS

The impacts of different pricing schemes are investigated for three different scenarios. The "**Base Scenario**" corresponds to a realistic simulation of the city of Austin and surroundings (Figure 4), comprising a considerable portion of the Austin metropolitan area (Greater Austin). The studied region, which includes satellite cities such as Round Rock, Cedar Park, and Pflugerville accounts in total for a population over 2 million (U.S. Census Bureau, 2017). The simulation's high-resolution navigation network includes 148,343 road segments (links). The population and agents' travel plans (activity chains) were obtained by adjusting Liu et al.'s (2017) year-2020 household data (based on the metropolitan transportation agency's 2020 trip tables and demographic data). Although the plans have not been formally validated, they have been adjusted to achieve realistic modal share, trip distances and durations. More than 100 types of trip-chain profiles deliver 3.5 trips per traveler per day. Each traveler (or active agent for that day) needs to travel at least once to execute his/her plans. Instead of simulating the full population, a sample of 5% (equivalent to 45,000 agents) is used here. A simulation of 150 iterations of such sample would still require between 12 and 20 hours on a super-computer. Link capacities are downsized to match the sample size. The available transportation modes (for regular, passenger travel) in the Base Case are conventional cars/passenger vehicles, 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 have access to car (either as a driver or passenger). In the simulations, public transit is assumed available to any traveler, although in some of the most peripheral areas, access and waiting times might be very poor.

FIGURE 4 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, to represent these distinctive 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 lower than 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 ($0.50 flat charge, 0.40 $/mile distance charge and 0.10 $/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 which cost corresponds to $0.20 per mile). Furthermore, we assume a decrease of availability of privately owned vehicles to 60% in order to reflect a decrease of ownership (Litman, 2017). 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 5. 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 and active mode trips decrease generating an overall increase of VMT (Table 1).

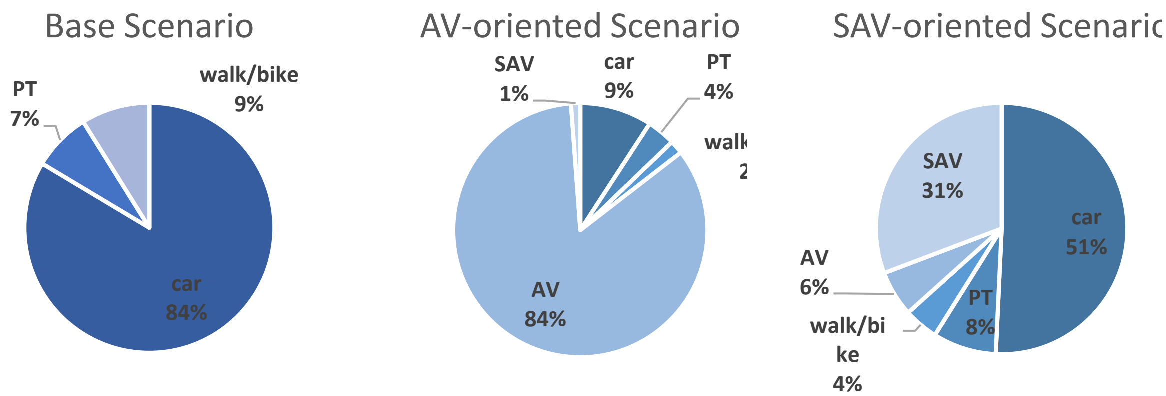

FIGURE 5 Modal split across three different scenarios

TABLE 1 Traffic Conditions of the Three Different Scenarios

	Base Scenario	AV-Oriented Scenario	SAV-Oriented Scenario
Total Daily VMT	2,671,560 mi/day	3,104,043	3,271,169
VMT by Empty SAVs	0	4,741	201,828
Total Travel Delay	251,475 veh-hr/day	405,854	469,123

CONGESTION PRICING STRATEGIES

This study investigates the performance of four different congestion pricing strategies. A facility-based and distance-based scheme are considered "traditional schemes", since they are well known in academia and in practice. A link-based marginal-cost-pricing scheme and a travel-time-congestion dependent scheme are considered "advanced schemes", because they are more complex and require relatively new technologies (such as those of connected-automated vehicle) for optimal implementation. Because of that, the advanced schemes are assumed to be implemented only in the AV-Oriented and SAV-Oriented scenarios.

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, 4,850 links in the AV-Oriented Scenario, and 4,424 links in the SAV-Oriented Scenario). As illustrated in Figure 6, the tolled links include the most important segments of Austin's highway system, including Interstate 35 and the State 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. The value has been derived by testing different levels of toll from \$0.10/link to \$0.50/link in the Base Scenario and selecting the most effective one in terms of delay reduction and the sum of travelers' monetized utility differences. Texan toll roads have varying charges between \$0.20 and \$1+ per mile, although they are limited to small portions (25 highway sections summing to less than 200 centerline-miles) with revenues mainly used for future road projects and maintenance (Formby, 2017).

Here, the **Distance-based Scheme**'s toll varies simply with distance traveled, at a rate of $0.10 per mile between the hours of 7 AM and 8 PM. This toll was chosen to maximize effectiveness and agents' utility, as discussed above, for the Link-Based scheme. One could make it more time or location dependent, requiring on board GPS to keep track of each vehicle's 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 et al. (2018) discuss such tolling options, and the strengths and weaknesses of various tolling technologies.

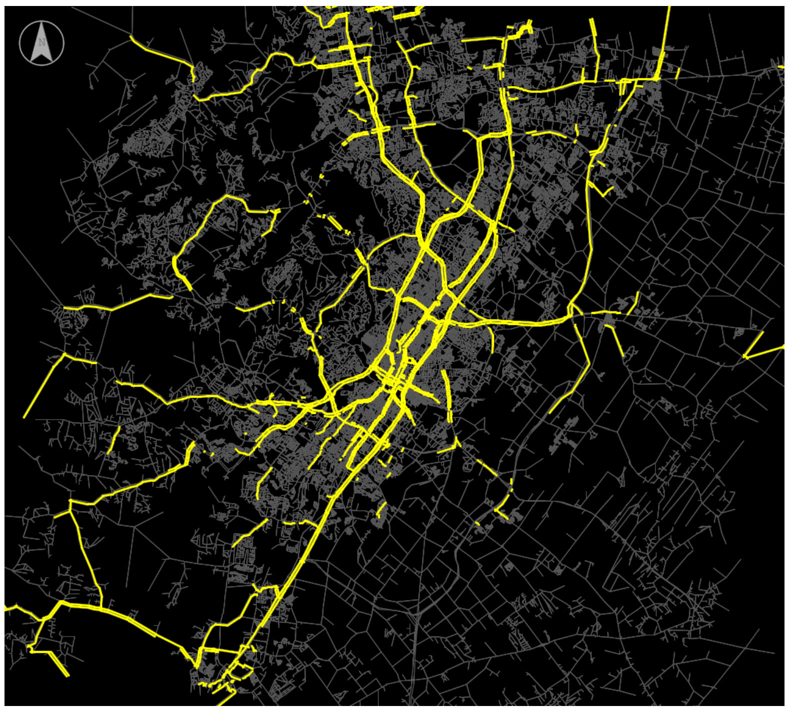

FIGURE 6 Selected links in the link-based scheme for the base scenario (source VIA:Senozon)

Advanced congestion pricing strategies

The first advanced congestion pricing strategy investigated consists of a dynamic marginal cost pricing (MCP) scheme at link level. In the context of road usage, MCP means charging users for the extra cost (shadow cost) that their trip causes to other travelers (Walters, 1961) due to lower travel times. According to MCP models, an optimal, static, link-based toll τ can be derived for each link such that:

$$\tau = V \cdot \frac{\partial c}{\partial V} \tag{5}$$

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, including the dynamic nature of congestion and the difficulty of setting operationally (and socially) optimal link tolls across 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 this "**MCP-based scheme"** proposed, each link's cost of congestion is derived using the Fundamental Diagram (FD), which is a relation between traffic throughput (or outflow) q (veh/h) and density k (veh/km) (Greenshields et al., 1935). According to the FD, the throughput increases with density until reaching the critical density corresponding to the link's capacity. For values of density above the critical ones, the link's throughput and (average) speed fall toward zero. Based on this concept, it is possible to estimate for each link, during a certain time interval, the amount of delay and corresponding toll such that queues can be eliminated and the traffic throughput adjusted to capacity.

Since MATSim reflects FD behavior, one can derive each link's average speed $u(k, q)$ as function of its traffic density and outflow, as follows:

$$u(k, q) = \frac{q}{k} \tag{6}$$

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

$$d = \left[\left(\frac{l}{u_{t+\Delta t}} - \frac{l}{u_t}\right) \cdot n\right] \tag{7}$$

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, and the second term n corresponds to the link users (vehicles) per time interval. The number of additional users (of the link) Δn over the time interval (only in case of decrease of outflow and speed) can be derived as:

$$\Delta n = (q_t - q_{t+\Delta t}) \cdot \Delta t \tag{8}$$

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

$$\tau_m = max\left\{0; \frac{d_m \cdot VTTS}{\Delta n_m}\right\} \tag{9}$$

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 comes from aggregating traffic condition measurements across 5 minute intervals. The toll has a maximum threshold value of $0.30. For practical reasons, given the size of the network, a subset of 15,020 centrally-located links are analyzed here, as shown in Figure 6.

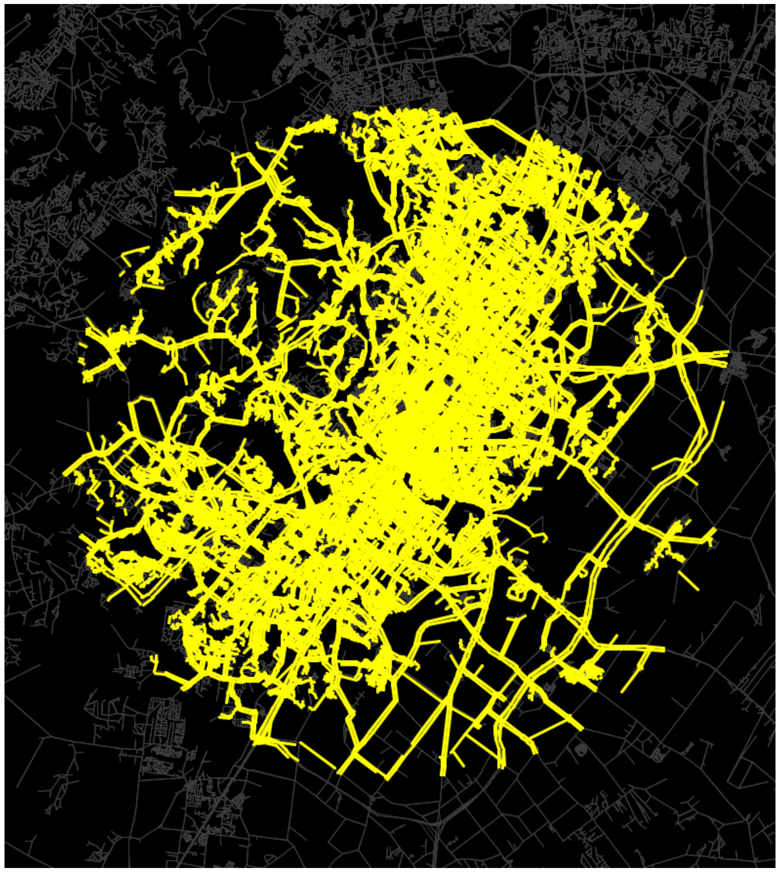

FIGURE 7 Analyzed links in the MCP scheme (source VIA:Senozon)

The second advanced congestion pricing scheme is a joint **"Travel Time-Congestion-based scheme."** The main rationale behind this approach lies in the fact that simple, distance-based strategies do not reflect traffic dynamics. They can even be detrimental, if drivers are incentivized to take shorter (but more congestible) routes (Liu et al., 2014). Charging users for the delay caused (at network level) during their time traveled, depending on the time of the day and on traffic conditions of the network could obviate this problem. Hence, trips made during the more congested times will be more penalized because of longer travel times and higher tolls. Similar to transportation network companies' (TNC) surge-pricing policies, where prices vary with demand-supply ratios, in the Travel Time-Congestion-based scheme dynamic tolls are derived as follows:

$$\tau = \alpha \cdot \sigma_{[t,t+\Delta t]}(t) \tag{10}$$

where α is a constant proportional parameter, which influences the rate of achieving the optimal toll, and σ is the network congestion dependent component. A conservative value of $\alpha = 0.1$ is assumed in both scenarios. The component $\sigma_{[t,t+\Delta t]}(t)$ varies every 30 minutes, based on traffic conditions measured across all six 5-min intervals in that half hour. In order to reflect changes of overall marginal cost of congestion on the network, the travel-time-congestion-dependent component is derived as follows:

$$\sigma_{[t,t+\Delta t]} = \frac{(\sum_i^M d_m) \cdot VTTS}{S \cdot r} \tag{11}$$

where link m's delay d_m is calculated using Eq. 7 for the networks' M links, 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:

$$r = \frac{L}{U} \tag{12}$$

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

Since both advanced schemes seek 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 of the vector of tolls $\bar{\tau}$ for all the links considered. Given the complexity of the problem, two stopping criteria are used here. The first one, similarly to Lin et al.'s approach (2008), uses the average difference of travel time of trip (for each agent) as follows:

$$\Delta TT = \frac{1}{J} \cdot \sum_{j}^{J} \sum_{i}^{I} \frac{\left| tt_{i,j}^{k-1} - tt_{i,j}^{k} \right|}{tt_{i,j}^{k}} \cdot 100$$

where $tt_{i,j}^{k}$ corresponds to the travel time of agent's j trip i in iteration k. The second stopping criterion corresponds to the average change of agents' utilities, ΔU. Hence, for each iteration j, the algorithm performs the following steps:

- Identify toll values $\overline{\tau_j}$ 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 the average difference of travel time of trip ΔTT and agents' utilities ΔU between the current iteration j and the previous (j-1).
- Check if both meet the objective value. If yes, stop. Otherwise, return to step 1.

Owing to computational limitations, only 150 iterations per simulation of MATsim could be run with the developed code. The results between the final and penultimate iterations have scores within 5% of each other, although route choices may still vary in the links used be very few agents per time interval. Even though these results are suboptimal, they can be assumed close to the final route choices.

The resulting tolls for the MCP-scheme for the AV-Oriented and SAV-Oriented Scenario are determined after 10 to 15 simulations (Figure 8). Among the 28,484 links analyzed, between 5,000 and 7,000 are tolled (across the various 15-min intervals), with an average charge between $0.02-$0.05 (per link) in each scenario.

Figure 9 illustrates tolls for the Travel Time-Congestion-based scheme for both the AV-Oriented and SAV-Oriented Scenarios. The two schemes show similar trends in the variation of the travel time toll during the peak hours, with higher charges during the morning peak. As expected, since AV travel costs are lower than SAV travel costs, the resulting levels of charge in the AV-Oriented Scenario are higher than in the SAV-Oriented Scenario.

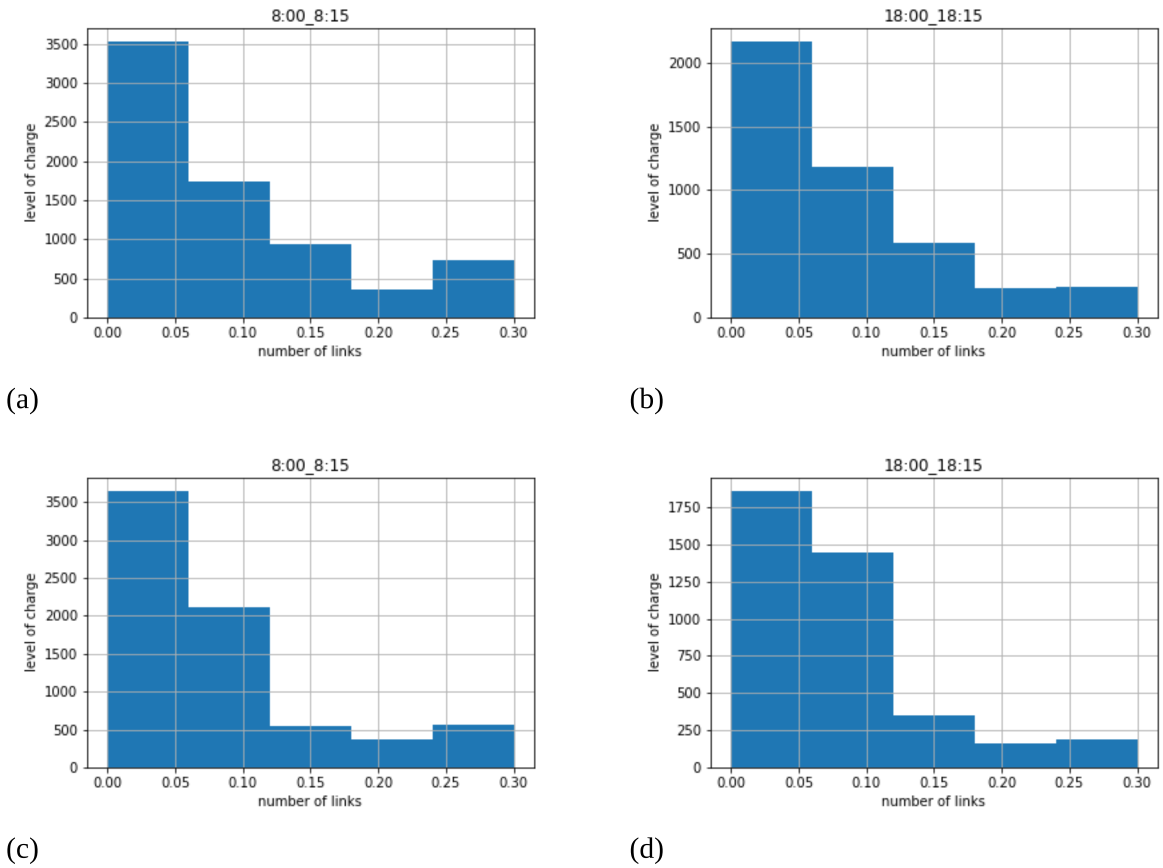

FIGURE 8 Toll distribution during the morning peak and evening peak in the AV-oriented scenario (a-b) and SAV-oriented scenario (c-d)

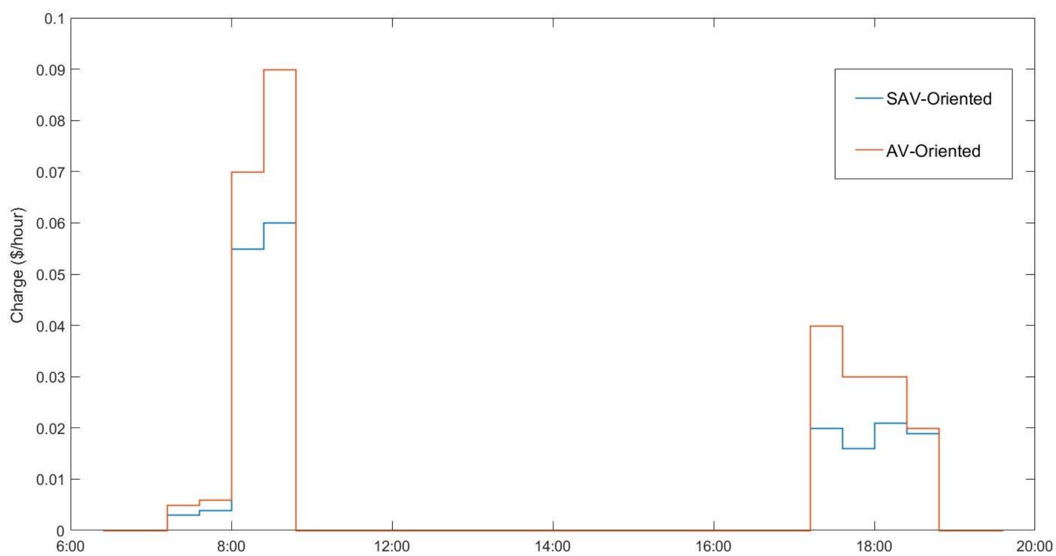

FIGURE 9 Resulting tolls for the travel time-congestion based scheme in the AV-oriented and SAV-oriented scenario

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 congestion-pricing strategies evaluated here succeed in reducing car, AV and SAV trips, with the exception of the Travel Time-Congestion-based scheme. Overall, PT and slow modes witness an increase in mode share (Table 2), as expected – due to making road use more expensive.

Overall, the demand for conventional vehicles seems more elastic than the demand for AVs and SAVs given the higher modal shift achieved for all the CP strategies. Because of their higher initial costs, car travelers are more incentivized than AV travelers to adopt PT or slow modes in the presence of tolls. SAVs users, face higher cost than AVs, so they are generally more responsive to tolls. For this reason, CP strategies seem to be more effective in the Base Scenario (no AV-SAVs) and the SAV-Oriented Scenario.

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, the scenarios characterized by large presence of AVs and SAVs differ from each other in their modal shifts. While in the SAV-Oriented Scenario the two schemes have comparable effects, in the AV-Oriented Scenario the Link-based scheme reduces AV trips more than the Distance-based scheme does. This is an interesting outcome, since the two schemes are conceptually very different from one another and could have very different effects in terms of economic gains, distributional effects, and public acceptability.

The MCP-based scheme determines less travel behavior changes than the ones achieved with the traditional Link-based scheme, since the average levels of charge are lower. The Travel Time-Congestion based scheme does not yield any reduction of private trips in either scenario.

TABLE 2 Modal Share from the Different CP Schemes

		AV Oriented	SAV Oriented	Base (no SAVs-AVs)
Link-based scheme	Car trips (%)	8.55	46.14	76.57
	PT trips (%)	16.66	20.97	13.26
	Walk/bike trips (%)	6.61	9.20	10.16
	AV trips (%)	67.55	4.86	0.00
	SAV trips (%)	0.61	18.81	0.00
Distance-based scheme	Car trips (%)	8.53	47.51	69.06
	PT trips (%)	4.93	14.95	10.07
	Walk/bike trips (%)	2.48	7.12	20.85
	AV trips (%)	83.25	5.82	0.00
	SAV trips (%)	0.78	24.54	0.00
MCP-based scheme	Car trips (%)	8.49	47.37	-

	PT trips (%)	11.05	17.26	-
	Walk/bike trips (%)	4.93	8.38	-
	AV trips (%)	74.85	5.40	-
	SAV trips (%)	0.66	21.56	-
Travel Time-Congestion scheme	Car trips (%)	9.27	51.5	-
	PT trips (%)	3.61	7.10	-
	Walk/bike trips (%)	1.79	4.05	-
	AV trips (%)	84.7	5.95	-
	SAV trips (%)			

Network performance

Both traditional and advanced CP strategies determine a significant reduction of private trips traveled by AVs, SAVs and cars (Figure 10). Schemes with a distance dependent fee component do not necessarily achieve the highest VMT reduction. 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. Vice versa, the Distance-based scheme seems to yield higher improvements in the Base Scenario and SAV-Oriented scenario. The Travel Time-Congestion based scheme has almost negligible effects on travel demand in both the AV-Oriented and the SAV-Oriented scenario.

However, this is just one perspective to evaluate the effects of road pricing strategies, as the changes in terms of network daily travel delay show (Figure 11). The results vary significantly according by strategy and scenario. Interestingly, in scenarios characterized by presence of AVs and SAVs, CP strategies targeting the critical links (i.e., the Link-based schemes) generate higher delay reductions than the distance-based scheme. In the Base Scenario however, the Distance-Based scheme achieves a higher delay reduction (in line with VMT reductions). This result can be partially explained by the fact that long AV-SAV trips (that would be affected by higher distance-based charges) are less incentivized to switch to low-quality modes like PT. Furthermore, the Distance-Based charge has been optimized based on Base Scenario results. Advanced CP schemes seem to achieve equal or higher travel delay reductions than traditional CP schemes. For example, the MCP-based scheme outperforms the corresponding traditional link-based scheme with reductions higher by 2 to 5 percentage points depending on the scenario. The Travel Time-Congestion-based scheme determines comparable reductions of delays to the corresponding Distance-based scheme (but at lower modal shifts). Despite changes in the mode shift are lower in the AV-Oriented scenario than in other scenarios, the decrease of delay is similar. In this case, users seem to be more willing to reroute and reschedule their trips rather than switching to public transit or active modes.

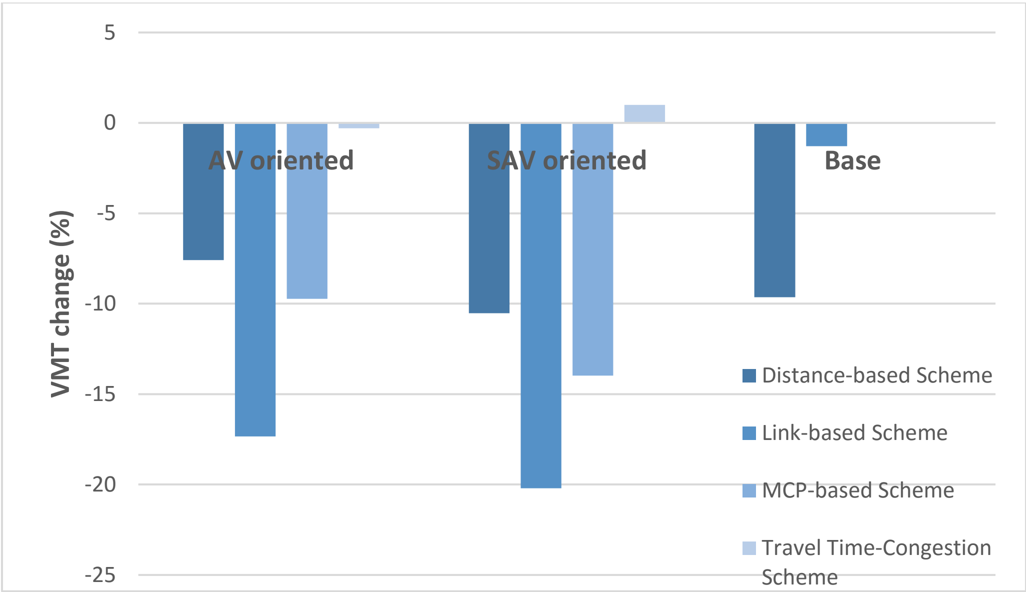

FIGURE 10 Reduction of motorized trips for the different scenarios according to the congestion pricing scheme

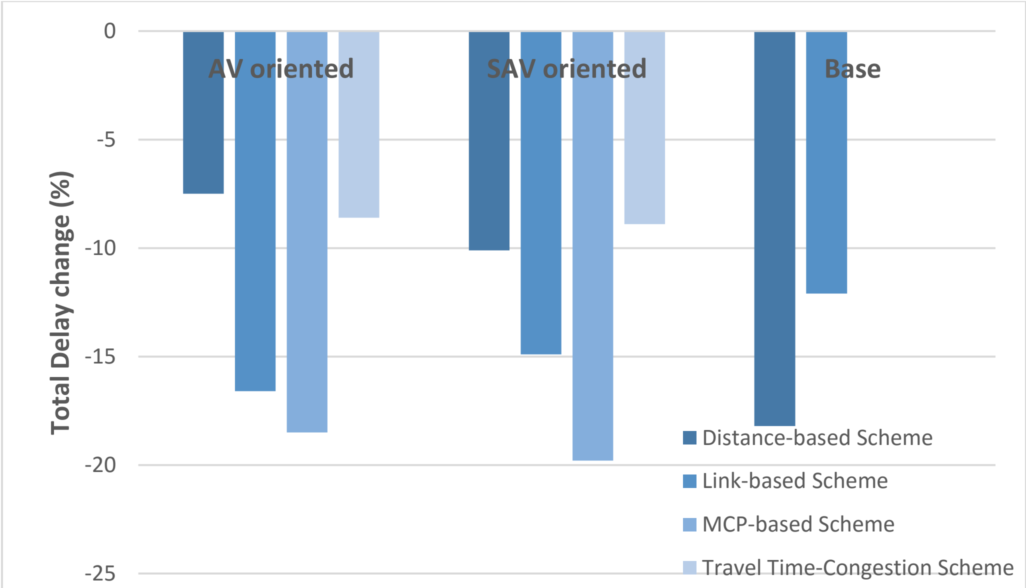

FIGURE 11 Reduction of traffic delay for the different scenarios according to the congestion pricing scheme

Welfare changes

Maximization of social welfare is important in evaluating transportation policy options. Table 3 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 MCP-based scheme, which performs similarly in all scenarios (assuming that the toll revenues could be fully reinvested). The Link-based scheme increases social welfare to a minor extent in the Base and AV-Oriented scenarios. In contrast, the Distance-based scheme is found to improve total social welfare only in the SAV-Oriented Scenario. The Travel Time-

Congestion based scheme yields welfare gains only in presence of high levels of SAVs as well. The high levels of congestion of the autonomous scenarios, the lower attractiveness of PT and active modes as compared to autonomous transport, and the relatively long commute make distance and travel time dependent tolls inefficient. Interestingly, the advanced CP strategies seem to yield higher welfare improvements compared to the corresponding traditional ones. The MCP-based toll and Travel Time-Congestion respectively outperform the Link-based scheme and Distance-based scheme. Finally, social welfare changes in future scenarios characterized by different market developments of autonomous driving compare differently with the Base Scenario according to the typology of CP scheme.

When the revenues are not considered, all of the CP strategies achieve a reduction in social welfare, with the exception of the Travel Time-Congestion scheme in the SAV-Oriented scenario. In this case, the highest performance (in terms of the lowest reduction of consumer surplus) is achieved by the Distance-based scheme in the AV-Oriented scenario and by Travel Time-Congestion Based Scheme in the 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, particularly from a public acceptance perspective.

TABLE 3 Welfare Changes for Alternative CP Schemes for Each Scenario

	AV-oriented Scenario	**SAV-oriented Scenario**	**Base Scenario**
Original Scenario-total welfare (Million $/day)	7.264	5.340	14.242
Link-Based Scheme: consumer surplus change ($ per capita per day)	-3.10	-1.72	-0.38
Link-Based Scheme: welfare change with revenues ($ per capita per day)	0.08	-0.02	0.02
Link-Based Scheme: Total welfare change (%)	**0.48**	**-0.11**	**0.12**
Distance-Based Scheme: consumer surplus change ($ per capita per day)	-1.70	-1.39	-1.01
Distance-Based Scheme: welfare change with revenues ($ per capita per day)	-0.66	0.18	-0.23
Distance-Based Scheme: Total welfare change (%)	**-3.92**	**1.25**	**-1.53**
MCP-Based Scheme: consumer surplus change ($ per capita per day)	-2.32	-1.37	-
MCP-Based Scheme: welfare change with revenues ($ per capita per day)	0.33	0.26	-
MCP-Based Scheme: Total welfare change (%)	**1.95**	**1.85**	-
Travel Time-Congestion Based Scheme: consumer surplus change ($ per capita per day)	-4.79	0.08	-
Travel Time-Congestion Scheme: welfare change with revenues ($ per capita per day)	-0.36	0.25	-
Travel Time-Congestion Scheme: Total welfare change (%)	**-2.11**	**1.75**	-

CONCLUSION

AVs and SAVs will affect people's mobility and traffic. In terms of congestion, it is not clear whether the benefits of increased accessibility and 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 (one characterized by high adoption of AVs, the other by wide usage of SAVs) for the metropolitan area of Austin. In the two future scenarios analyzed, vehicle-miles traveled (VMT) and traffic delays rise, due to mode shifts (away from traditional transit) and SAVs traveling empty.

From a traffic perspective, all the mobility schemes yield to considerable reductions of congestion. While advanced CP schemes are not necessarily more effective than traditional ones in affecting travel demand and traffic, they bring higher economic gains. More importantly, the effects of different strategies vary depending on the scenario. The Distance-based and Travel Time-Congestion based scheme seem more effective in the SAV-Oriented Scenario, while the Link-based scheme performs better in the AV-Oriented Scenario and in the Base Scenario. In all the scenarios, the MCP-based scheme yields to the largest 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, and the possibility of dropping activities in agents' plans. The implementation of SAV-based dynamic ride-sharing services, their traffic impacts and synergies with pricing strategies is another issue, which could be investigated in future research.

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.

AUTHOR CONTRIBUTION

The authors confirm the contribution to the paper as follows: study conception and design: M. Simoni and Kockelman, K.; Data analysis and interpretation of results: M. Simoni, K.M. Gurumurthy and J. Bischoff; Draft manuscript preparation: M. Simoni, K. Kockelman and K.M. Gurumurthy. All authors reviewed the results and approved the final version of the manuscript.

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