Effects of Autonomous Vehicle Behavior on Arterial and Freeway Networks

Rahul Patel, Michael W. Levin, and Stephen D. Boyles

Autonomous vehicles offer new traffic behaviors that could revolutionize transportation. Examples include reservation-based intersection control and reduced reaction times that result in greater road capacity. Most studies have used microsimulation models of those new technologies to study their impacts more realistically. However, microsimulation is not tractable for larger networks. Recent developments in simulating reservation-based controls and multiclass cell transmission models for autonomous vehicles in dynamic traffic assignment have allowed studies of larger networks. This paper presents analyses of several highly congested arterial and freeway networks to quantify how reservations and reduced reaction times affect travel times and congestion. Reservations were observed to improve over signals in most situations. However, signals outperformed reservations in a congested network with several close local road and arterial intersections because the capacity allocations of signals were more optimized for the network. Reservations also were less efficient than were traditional merges and diverges for on- and off-ramps. However, the increased capacity from reduced following headways resulted in significant improvements for both freeway and arterial networks. Finally, the authors studied a downtown network, including freeway, arterial, and local roads, and found that the combination of reservations and reduced following headways resulted in a 78% reduction in travel time.

Autonomous vehicles (AVs) offer new traffic behaviors that could revolutionize city transportation. New intersection controls (*1, 2*) could reduce intersection delays (*3, 4*), and adaptive cruise control, reduced reaction times, or both could similarly increase road capacity (*5, 6*). However, AVs could offset these improvements by increasing travel demand. Levin and Boyles found that allowing empty repositioning trips to avoid parking costs could result in overall increases in congestion (*7*). Furthermore, the Braess (*8*) and Daganzo (*9*) paradoxes demonstrate that improvements in capacity could increase congestion as a result of selfish route choice.

Most studies of AVs have relied on microsimulators to capture AV behavior differences, but microsimulation is not tractable for large network analyses. Carlino et al. simplified the reservation controls to simulate a city network, but the capacity of the reservation mechanism was reduced and route choice was not included (*10*). Ideally, analyses of large networks would be based on dynamic traffic assignment (DTA), which includes the effects of selfish route choice.

Department of Civil, Architectural, and Environmental Engineering, Cockrell School of Engineering, University of Texas at Austin, 301 East Dean Keeton Street, Stop C1761, Austin, TX 78712-1172. Corresponding author: M. W. Levin, michaellevin@mail.utexas.edu.

Transportation Research Record: Journal of the Transportation Research Board, No. 2561, Transportation Research Board, Washington, D.C., 2016, pp. 9–17.
DOI: 10.3141/2561-02

Levin and Boyles developed a conflict region simplification of the reservation protocol that is tractable for DTA (*11*) and a multiclass version (*12*) of the cell transmission model (CTM) by Daganzo (*13, 14*) with a corresponding car-following model that predicts increases in capacity and backward wave speed as reaction time decreases. The purpose of this paper is to use these DTA models to study how AVs affect larger networks.

The contributions of this paper are to use DTA to analyze the effects of reservation controls and increased capacity from AV technologies on freeway and arterial networks. The authors studied a variety of subnetworks from the 100 most congested roads in Texas and drew conclusions that can be generalized to other locations. For most scenarios, reservations were improved over traffic signals for arterial networks (and the freeway network that used signals to control access) but were not effective at replacing merges and diverges. Reduced reaction times, resulting in reduced following headways and increased capacity, improved travel times for all scenarios. The authors also studied the downtown Austin, Texas, network, which includes many route choice options, and found that the combination of these AV technologies could reduce travel times by 78%.

The remainder of the paper is organized as follows. Models of reservation-based intersection control are described, and the work of Levin and Boyles on a multiclass CTM model for AVs based on reaction time (*12*) is summarized. The effects of AVs on several arterial and freeway networks are analyzed, and then conclusions are presented.

INTERSECTION MODEL

Dresner and Stone proposed the reservation-based intersection protocol for AVs to use AV technologies to increase intersection utilization (*1, 2*). Traffic signals are not the most efficient use of intersection capacity because, during any phase, many turning movements are completely restricted. In moderate traffic, there may be gaps in the stream sufficient to move vehicles on conflicting turning movements. In addition, clearance intervals result in significant lost time per cycle. However, these are necessary to ensure safety for human drivers.

In reservation-based controls, vehicles communicate wirelessly with an intersection manager to request to move through the intersection at a specific time. The intersection manager simulates the request in a grid of space–time tiles and accepts or rejects the request depending on whether it conflicts with other reservations. When conflicts occur, most studies have used a first-come, first-served (FCFS) priority: the reservation of the vehicle that requested first is granted (*1–4*). However, alternative policies have also been studied, such as prioritizing emergency vehicles (*15*) or even holding an auction at each intersection to allow vehicles to bid to move first

(*16–18*), which was found to be an improvement over FCFS in some scenarios.

Results in work by Fajardo et al. (*3*), who used Dresner and Stone's AIM4 simulator, and Li et al. (*4*), who used Vissim, indicated that FCFS reservations could reduce delays beyond optimized traffic signals. However, most network-based studies have been limited by the computational complexity of the simulation of vehicles through the intersection space–time tiles in the reservation protocol. Microsimulation studies have therefore been limited to small networks (*19*) or have made major simplifications to the reservation protocol that reduced its capacity (*10*). Levin and Boyles addressed the computational issues by aggregating the tiles into conflict regions, illustrated in Figure 1, and replacing the simultaneous occupancy checks of the tile-based reservation protocol with capacity constraints (*11*).

At each time step, the conflict region algorithm considers the list of vehicles that are waiting and able to enter the intersection (S). This list is the set of vehicles that are at the intersection and at the front of their lane (so they are not blocked from moving by other vehicles). The algorithm then sorts S according to some priority function [$f(\cdot)$]. (For FCFS, the priority function is the reservation request time.) Next, the algorithm iterates through S until it finds a vehicle (v) that can move through the intersection. (Moving could be obstructed by conflict region capacity or receiving flow in the downstream link.) Vehicle v's reservation request is granted, and the vehicle waiting behind v is added to S in sorted order. The algorithm continues to look through S until none of the vehicles in S are able to move.

The conflict region model was shown to be tractable for DTA on city networks while retaining the simultaneous use characteristics of reservation controls. The purpose of this paper is to use the conflict region model, as well as the later multiclass CTM model of Levin and Boyles (*12*), to study how increasing use of AVs will affect the traffic efficiency of arterial and freeway networks.

The reservation protocol may also be extended for vehicles operated by humans, which have two potential issues when using a reservation system: two-way communication and following a reservation. For AVs, communication of reservation requests usually involves short-range wireless communications with the intersection manager. Humans might be able to inform the intersection manager of their request through a smartphone application. However, vehicles typically must communicate their estimated time of arrival at the intersection, which might not be known if there are vehicles in front. The protocol for using a smartphone application could be quite complex. To solve the communications issue, Dresner and Stone proposed inserting a cycling green light in the reservation protocol to allow vehicles operated by humans to move (*15, 20*).

In addition, following the reservation is difficult for vehicles operated by humans because of the required precision in speed, acceleration, and entrance time, and the vehicle's travel through the intersection to avoid conflicts with other vehicles. Humans following a smartphone application would have less precision and would therefore require greater safety margins than would AVs. Bento et al. (*21*) and Qian et al. (*22*) studied methods of integrating vehicles operated by humans into the reservation protocol directly. Bento et al. proposed reserving additional safety margins for human vehicles (*21*), and Levin and Boyles implemented this proposal into the conflict region model (*12*).

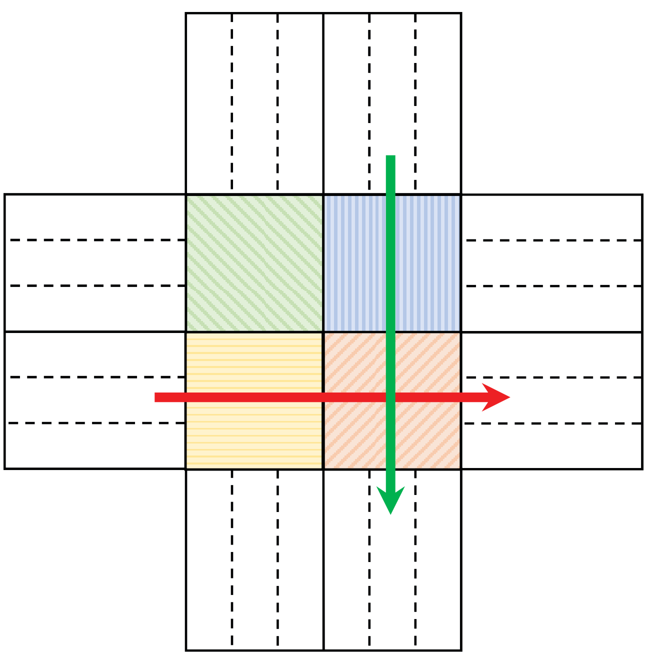


FIGURE 1 Conflict region representation of a four-way intersection with two conflicting turning movements.

FLOW MODEL

In addition to new intersection controls, connected vehicles or AVs could reduce reaction times, resulting in reduced following headways. Microsimulation studies of adaptive cruise control have observed increases in capacity (*5, 6*) and stability (*23, 24*). However, a microsimulation model is not tractable for city network modeling. This section summarizes the multiclass CTM model and fundamental diagram developed by Levin and Boyles to estimate capacity and backward wave speed as a function of vehicle class proportions and their reaction times (*12*). This model is used to propagate flow in the DTA analyses. For a complete discussion of the multiclass CTM conservation of flow and the effects of AV reaction times on capacity and backward wave speed, see work by Levin and Boyles (*12*).

Because the focus is on vehicles with identical or similar physical characteristics but different drivers, it was assumed that all vehicles have the same free-flow speed. Although all vehicles have the same free-flow speed, vehicles operated by humans and AVs respond differently to congestion because of different reaction times. AVs will maintain free-flow speed at higher densities than human vehicles would be able to and AVs have correspondingly higher capacity. In addition, congested shock waves propagate faster for AVs. In the cell discretization, a uniform distribution of class-specific density per cell was also assumed, although those densities may change with each time step. The model admits an arbitrary number of vehicle classes to be extensible to different levels of automation.

Multiclass CTM

Let M be the set of vehicle classes with class-specific density $k_m(x, t)$ at space–time point (x, t) and class-specific flow $q_m(x, t) = u(k_1/k, \ldots, k_{|M|}/k)\, k_m(x, t)$, a function of the speed $u(k_1, \ldots, k_{|M|})$ possible with class proportions of $k_1/k, \ldots, k_{|M|}/k$. Similarly, let $w(k_1/k, \ldots, k_{|M|}/k)$ be the backward wave speed function. Then speed is limited by free-flow speed, capacity, and backward wave propagation:

$$u\left(k_1,\ldots,k_{|M|}\right)=\min\left\{\begin{array}{l} u^{\mathrm{f}},\dfrac{q^{\max}\left(\dfrac{k_1}{k},\ldots,\dfrac{k_{|M|}}{k}\right)}{k}, \\ w\left(\dfrac{k_1}{k},\ldots,\dfrac{k_{|M|}}{k}\right)\left(k^{\mathrm{jam}}-k\right)\end{array}\right\} \tag{1}$$

where

u^{f} = free-flow speed,
$q^{\max}(k_1/k, \ldots, k_{|M|}/k)$ = capacity function, and
k^{jam} = jam density.

For the cell discretization, let $n_i^m(t)$ be the number of vehicles of class m in cell i at time t and $y_i^m(t)$ be the transition flow of class m from cell i to cell $i+1$ at time t. It is assumed that the fundamental diagram is trapezoidal, bounded by the free-flow speed u^{f}, cell-time specific capacity $Q_i(t)$, and cell-time specific backward wave speed $w_i(t)$:

$$y_i^m(t)=\frac{n_{i-1}^m(t)}{n_{i-1}(t)}\min\left\{\sum_{m\in M}n_{i-1}^m(t),Q_i(t),\frac{w_i(t)}{u^{\mathrm{f}}}\left(N-\sum_{m\in M}n_i^m(t)\right)\right\} \tag{2}$$

$$=\min\left\{n_{i-1}^m(t),\frac{n_{i-1}^m(t)}{n_{i-1}(t)}Q_i(t),\frac{n_{i-1}^m(t)}{n_{i-1}(t)}\frac{w_i(t)}{u^{\mathrm{f}}}\left(N-\sum_{m\in M}n_i^m(t)\right)\right\} \tag{3}$$

which shows that flow of class m is restricted by three factors: class-specific cell occupancy, proportional share of the capacity, and proportional share of congested flow. Variables $Q_i(t)$ and $w_i(t)$ are functions of the proportion of classes. These transition flows satisfy conservation of flow, consistent with the multiclass hydrodynamic theory (*12*).

When one is implementing this CTM, it is necessary for $w_i(t) \le u^{\mathrm{f}}$ so that the cell length is determined by the free-flow speed and not the backward wave speed. This requirement is usually satisfied by single-class flow, and may be satisfied for multiclass flow, depending on the reaction time chosen for the car-following model. In addition, assuming uniformly distributed density results in the possibility of non–first-in, first-out behavior within cells. However, as discussed by Blumberg and Bar-Gera, even single-class CTMs may violate first-in, first-out behavior at intersections (*25*).

Link Capacity and Backward Wave Speed

To determine $Q_i(t)$ and $w_i(t)$, the authors used the car-following model from Levin and Boyles that is based on kinematics and that predicts the safe following distance as a function of reaction time (*12*).

Backward wave speed increases as reaction time decreases, which is consistent with microsimulation results found by Schakel et al. (*24*). Capacity is

$$q^{\max}=\frac{u^{\mathrm{f}}}{u^{\mathrm{f}}\sum_{m\in M}\dfrac{k_m}{k}\Delta t_m+\ell} \tag{4}$$

where Δt_m is the reaction time of class m and ℓ is vehicle length. Backward wave speed is

$$w=-\frac{\dfrac{u^{\mathrm{f}}}{u^{\mathrm{f}}\sum_{m\in M}\dfrac{k_m}{k}\Delta t_m+\ell}}{\dfrac{1}{u^{\mathrm{f}}\sum_{m\in M}\dfrac{k_m}{k}\Delta t_m+\ell}-\dfrac{1}{\ell}}=\frac{\ell}{\sum_{m\in M}\dfrac{k_m}{k}\Delta t_m} \tag{5}$$

Figure 2 shows how the fundamental diagram changes with AV proportion when human drivers have a reaction time of 1 s (*26*) and AVs have a reaction time of 0.5 s for a link with free-flow speed of 60 mph. Figure 2 illustrates the flow model used for all links in the experiments. The specific fundamental diagram for each link depends on its free-flow speed and AV proportion.

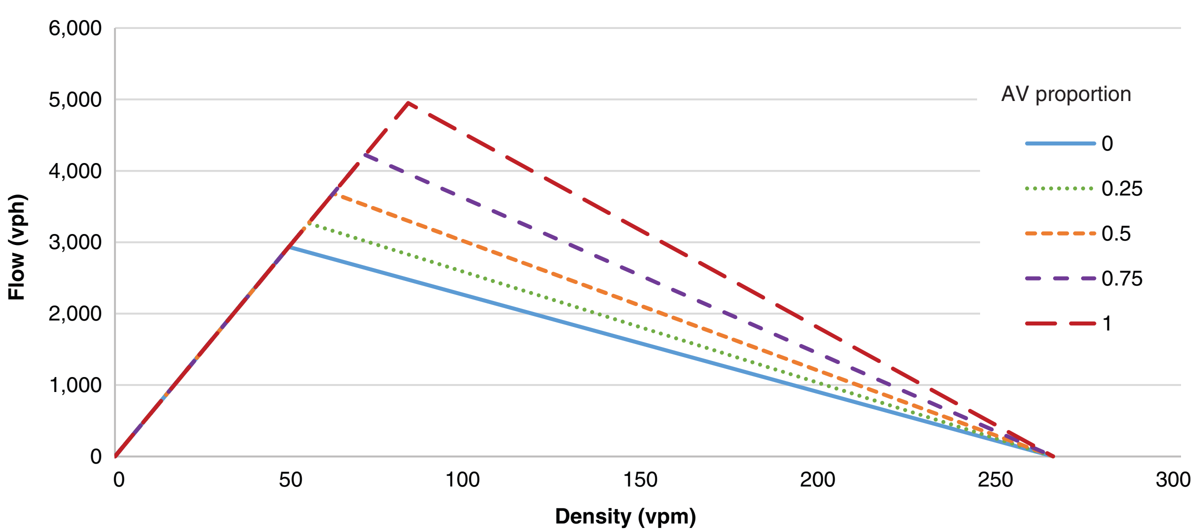


FIGURE 2 Fundamental diagram scaling with proportion of AVs with 0.5-s reaction time and 60 mph free-flow speed (vph = vehicles per hour; vpm = vehicles per mile).

As discussed by Levin and Boyles, capacity is affected by other factors, such as lane width and road condition (*12*). To integrate the capacity and backward wave speed predictions in Equations 4 and 5 into current CTM models, the authors scaled the estimated current capacity $\bar{q}^{\max}$ and backward wave speed $\bar{w}$ accordingly:

$$\tilde{q}^{\max} = \frac{u^{\mathrm{f}} \Delta t_{\mathrm{HM}} + \ell}{u^{\mathrm{f}} \sum_{m \in M} \frac{k_m}{k} \Delta t_m + \ell} \bar{q}^{\max} \tag{6}$$

$$\tilde{w} = \frac{\Delta t_{\mathrm{HM}}}{\sum_{m \in M} \frac{k_m}{k} \Delta t_m} \bar{w} \tag{7}$$

where Δt_{HM} is the reaction time for human drivers. The variables $\tilde{q}^{\max}$ and $\tilde{w}$ are then used to determine flow for the trapezoidal fundamental diagram in CTM.

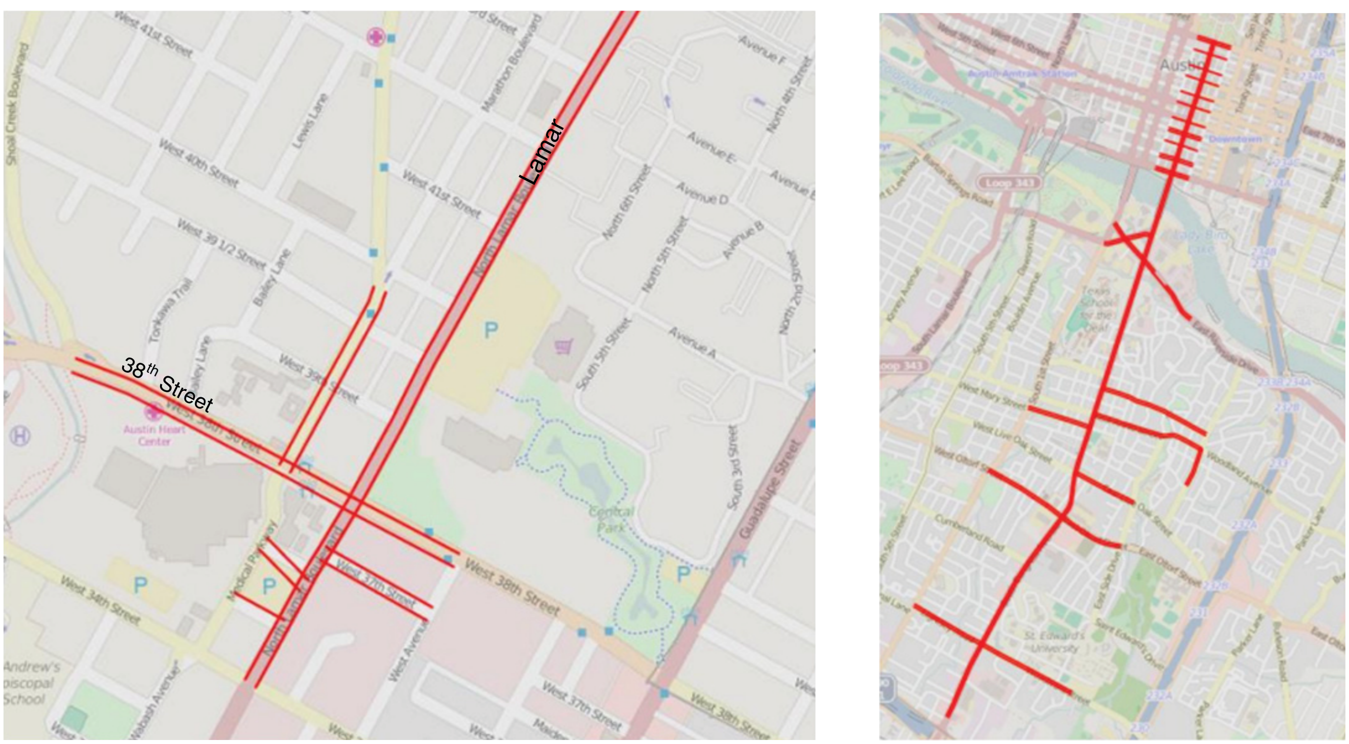
EXPERIMENTAL RESULTS

This section presents analyses of arterial, freeway, and downtown networks; the analyses used the multiclass CTM to propagate flow in DTA. The key features of these results are the multiclass comparison of vehicles operated by humans and AVs, and the analysis of how reservations compare with signals. The fundamental diagram changes with space and time in response to the proportion of AVs in each cell. When combined with discrete vehicles, the fundamental diagram varies significantly between cells and time steps despite an overall fixed proportion of AVs. Reservation-based intersection control also exhibited unusual characteristics. Contrary to the results of Fajardo et al. (*3*) and Li et al. (*4*), reservations performed worse than did signals in many scenarios because of suboptimal vehicle priority. In addition, Daganzo showed that the increasing capacity from AVs does not necessarily result in improved network performance (*27*).

The arterial and freeway networks do not have multiple available routes, so all improvements are because of AV technologies. However, the downtown network includes many alternative routes, which admits paradoxes in which capacity improvements increase congestion as a result of selfish route choice (*8, 9*). The reaction times of AVs was set to 0.5 s, which significantly increases capacity (Figure 2). Smaller reaction times might be more realistic for automation, but could result in backward wave speed exceeding free-flow speed, which would cause technical issues with the CTM. For all experiments, the authors recorded the total system travel time, as well as the average travel time per vehicle.

Arterial Networks

The paper first presents results on two arterial networks in Austin, shown in Figure 3. The first arterial network, Lamar Boulevard and 38th Street, contains the intersection between the Lamar Boulevard and 38th Street arterials, as well as five other local road intersections. This network contains 31 links, 17 nodes, and five signals, with a total demand of 16,284 vehicles over a 4-h period. The authors also studied Congress Avenue in Austin, with a total of 25 signals in the network, 216 links, and 122 nodes, with a total demand of 64,667 vehicles in 4 h. These arterial networks used fixed-time signals for controlling flow along the entire corridor. These networks were chosen for this experiment because they were among



(a) (b)

FIGURE 3 Arterial networks: (*a*) Lamar Boulevard and 38th Street and (*b*) Congress Avenue.

the 100 most congested networks in Texas and are useful for studying how AVs affect congestion. By changing the demand on these networks, researchers can generalize the analyses to less congested networks.

Travel time results for arterial networks are shown in Table 1. The general trend for the arterial networks is that the use of the reservation protocol reduced travel times. Reservations help most arterial networks, such as Congress Avenue. At high demands, the reservations increased travel times for Lamar Boulevard and 38th Street. The lower 0.5-s reaction time for AVs compared with the 1-s reaction time for vehicles operated by humans decreased travel times for every network tested. As the proportion of AVs in the network was increased, the travel times decreased. Reduced reaction times were more beneficial in some scenarios than in others, but all saw a benefit. The reaction time difference was analyzed by running simulations of each demand proportion at 0% and 100% AVs.

In the Lamar Boulevard and 38th Street network, the reservation protocol significantly decreased travel times for a 50% demand simulation as compared with traffic signals at 50% demand; however, once the demand was increased to 75%, reservations began to increase travel times relative to signals. This result is most likely because of the close proximity of the local road intersections. On intersections of local roads with arterials, the fairness attribute of FCFS reservations could give greater capacity to the local road than would traffic signals. Because these intersections are so close together, reservations likely induced queue spillback on the arterial. The longer travel times might also be influenced by reservations removing signal progression on 38th Street. In high congestion, FCFS reservations tended to be less optimized than signals for the local road and arterial intersections. However, in low demand, intersection saturation was sufficiently low for reservations to reduce delays.

The Lamar Boulevard and 38th Street network responded well to an increase in the proportion of AVs with dramatic decreases in travel times because of the AV reaction times. At 85% demand and at 25% AVs, the total travel time was reduced by 50%, and when all vehicles were AVs, the total travel time was reduced by 87%. As demand increased, the improvements from reduced reaction times also increased. At 50% demand, reduced reaction times decreased travel time by 44%, whereas at 100% demand, reduced reaction times decreased travel time by 93%. The effect of greater capacity improved as demand increased because as demand increased, the network became more limited by intersection capacity. At low congestion (50% demand), signal delays dominated travel times because reservations made significant improvements. At higher congestion, intersection capacity was the major limitation, and therefore reduced reaction times were of greater benefit.

Congress Avenue responded well to the introduction of reservations, showing decreases in travel times in all demand scenarios. These improvements are a result of the large number of streets intersecting Congress Avenue, each with a signal not timed for progression. The switch to reservations therefore reduced the intersection delay. However, the switch to reservations could result in greater demand on this arterial. The authors include the effects of route choice in the analysis of the downtown Austin network.

AVs also improved travel times and congestion as a result of reduced reaction times. At 85% demand, even a 25% proportion of AVs on roads decreased travel times by almost 60%. This figure increased to almost 70% when all vehicles were AVs. As with Lamar Boulevard and 38th Street, as demand increased, the improvements from AV reaction times also increased. For example, at 50% demand, 100% AVs decreased travel time by about 10%, but at 100% demand, using all AVs reduced the travel time by nearly 82%. The reduced reaction times did not improve as much as did the reservation protocol, except for the 100% demand scenario. This result indicates that at lower demands, travel time was primarily increased by signal delay but was still improved by AV reaction times.

Overall, these results consistently show significant improvements from reduced reaction times of AVs at all demand scenarios. As shown in Figure 2, reducing the reaction time to 0.5 s nearly doubles road and intersection capacity. However, the effects of reservations were mixed. At low congestion, traffic signal delays had a greater effect on travel time, and in these scenarios reservations improved. Reservations also improved when signals were not timed for progression (although this setup may be detrimental to the overall system). However, as seen on Lamar Boulevard and 38th Street, at high demand, reservations performed worse than signals, especially around local road and arterial intersections.

TABLE 1 Arterial Network Results

Intersection Control	Demand (%)	Proportion of AVs	TSTT (h)	Travel Time per Vehicle (min)
Lamar Boulevard and 38th Street				
Signals	50	0	421.6	3.11
Signals	50	1	237.2	1.75
Reservations	50	1	157.8	1.16
Signals	75	0	2,566.7	12.61
Signals	75	1	372.7	1.83
Reservations	75	1	2,212.5	10.87
Signals	85	0	3,890.2	16.86
Signals	85	0.25	2,097.2	9.09
Signals	85	0.5	504.8	2.19
Signals	85	0.75	477.8	2.07
Signals	85	1	476.8	2.07
Reservations	85	1	4,472.8	19.39
Signals	100	0	7,043.1	25.95
Signals	100	1	526.6	1.94
Reservations	100	1	8,678.7	31.98
Congress Avenue				
Signals	50	0	1,366.1	2.54
Signals	50	1	1,220	2.26
Reservations	50	1	821.5	1.52
Signals	75	0	4,306.1	5.33
Signals	75	1	1,957.1	2.42
Reservations	75	1	1,545.1	1.91
Signals	85	0	8,976.8	9.8
Signals	85	0.25	3,661.4	4
Signals	85	0.5	3,303.3	3.61
Signals	85	0.75	2,936.2	3.21
Signals	85	1	2,956	3.23
Reservations	85	1	2,934	3.2
Signals	100	0	21,484.4	19.93
Signals	100	1	4,038.2	3.75
Reservations	100	1	8,673.6	8.05

NOTE: TSTT = total system travel time.

Freeway Networks

Next, the authors studied three freeway networks, shown in Figure 4. The first freeway network is the I-35 corridor in the Austin region, which includes 220 links and 220 nodes, with a total demand of 128,051 vehicles within a 4-h span. All intersections are off-ramps

(a) (b) (c)

FIGURE 4 Freeway networks: (*a*) I-35, (*b*) US-290, and (*c*) Mopac Expressway.

or on-ramps. (Because of the network length, the on- and off-ramps are difficult to see in the image.) The I-35 network is by far the most congested of the freeway networks and one of the most congested freeways in all of Texas, especially in the Austin region. The authors also studied the US-290 network in the Austin region, with 97 links, 62 nodes, five signals, and a total demand of 11,098 vehicles within 4 h. Finally, the authors studied the Mopac Expressway in the Austin region, with 45 links, 36 nodes, and four signals, with a total demand of 27,787 vehicles within 4 h. This network includes a mix of merging and diverging ramps and signals, which provides for some interesting analyses. This network was chosen because of the large number of signals around the freeway. All freeway networks are among the 100 most congested roads in Texas.

Results for the freeway networks are presented in Table 2. Although there were some observed improvements in travel times for US-290 when reservations were used, the improvements were modest. For I-35 and Mopac Expressway, reservations made travel times worse for all demand scenarios. Most of the access on US-290 is controlled by signals, which explains the improvements observed when reservations were used there. Reservations seem to have worked more effectively with arterial networks, probably because on- and off-ramps do not have signal delays. Therefore, the potential for improvement from reservations is smaller.

Overall, greater capacity from the reduced reaction times of AVs improved travel times in all freeway networks tested, with better improvements at higher demands. Reduced reaction times improved travel times by almost 72% at 100% demand on I-35. On US-290 and I-35, as with the arterial networks, the improvement from AV reaction times increased as demand increased. This result is because freeways are primarily capacity restricted. On Mopac Expressway, reaction times had a smaller impact, but the network overall appeared to be less congested.

The authors also analyzed several groups of links and nodes in depth. Links and nodes were chosen to study how reservations affected travel times at critical intersections, such on- or off-ramps with high demand. For these specific links, the authors compared average link travel times between 120 and 135 min into the simulation, at the peak of the demand. The authors compared vehicles operated by humans, AVs with signals, and AVs with reservations at 85% demand, which resulted in moderate congestion. In the I-35 network, very few changes in travel times for the critical groups of links were observed from the different intersection controls.

The differences seemed to be greater in the US-290 corridor, with more overall improvements in critical groupings of links near intersections. The largest improvements in travel times going from traffic signals to reservations occurred at queues for right turns onto the freeway. A possible explanation for this result is that making a right turn conflicts with less traffic than going straight or making a left turn. Although signals often combine right-turn and straight movements, reservations could combine turning movements in more flexible ways. Although larger improvements in travel times occurred at the observed right turns, improvements at left turns were also observed. Because US-290 has signals intermittently spaced throughout its span, vehicles are frequently stopping for signal delays. With the reservations system, the flow of traffic is stopped less frequently, reducing congestion. The use of AVs rather than vehicles operated by humans also helped travel times, but by less than reservations did. In most cases, using reservations instead of signals doubled the improvements resulting from using AVs. Reservations appear to have a positive effect on traffic flow and congestion in networks (freeway and arterial) that use signals to control intersections.

Downtown Network

The authors tested the downtown network of Austin, shown in Figure 5, with 100% demand, at different proportions of AVs. Downtown Austin differs from the previous networks in that there are many route choices available. Therefore, the authors solved DTA by using the method of successive averages. All scenarios were

TABLE 2 Freeway Network Results

Intersection Control	Demand (%)	Proportion of AVs (%)	TSTT (h)	Travel Time per Vehicle (min)
I-35				
Traditional	50	0	3,998.9	3.75
Traditional	50	100	3,893.3	3.65
Reservations	50	100	3,975.2	3.73
Traditional	75	0	10,087	6.3
Traditional	75	100	5,934.2	3.71
Reservations	75	100	9,861.1	6.16
Traditional	85	0	16,127.7	8.89
Traditional	85	25	16,023.5	8.83
Traditional	85	50	15,944.3	8.79
Traditional	85	75	14,545.3	8.02
Traditional	85	100	14,101.6	7.77
Reservations	85	100	16,084.7	8.87
Traditional	100	0	31,611.7	14.81
Traditional	100	100	9,063.3	4.25
Reservations	100	100	30,211.3	14.16
Mopac Expressway				
Traditional	50	0	373.9	1.61
Traditional	50	100	363.6	1.57
Reservations	50	100	409.9	1.77
Traditional	75	0	576.6	1.66
Traditional	75	100	554.9	1.6
Reservations	75	100	616.1	1.77
Traditional	85	0	667.9	1.7
Traditional	85	25	651.1	1.65
Traditional	85	50	647.8	1.65
Traditional	85	75	645.2	1.64
Traditional	85	100	644.1	1.64
Reservations	85	100	698.7	1.77
Traditional	100	0	1,288.3	2.78
Traditional	100	100	752.1	1.62
Reservations	100	100	825.4	1.78
US-290				
Traditional	50	0	557.8	6.03
Traditional	50	100	547.5	5.92
Reservations	50	100	505.4	5.47
Traditional	75	0	845.7	6.1
Traditional	75	100	827.7	5.97
Reservations	75	100	759.8	5.48
Traditional	85	0	997.6	6.35
Traditional	85	25	952	6.06
Traditional	85	50	945.3	6.01
Traditional	85	75	942.5	6
Traditional	85	100	939.8	5.98
Reservations	85	100	860.6	5.47
Traditional	100	0	1,518.5	8.21
Traditional	100	100	1,108.8	5.99
Reservations	100	100	1,014.1	5.48

solved to a 2% gap, which was defined as the ratio of average excess cost to total system travel time. Route choice admits issues such as the Braess (*8*) and Daganzo (*9*) paradoxes, in which capacity improvements induce selfish route choices that increase travel times for all vehicles. The downtown network also contains both freeway and arterial links, with part of I-35 on the east side, a grid structure, and several major arterials.

Results from the analysis of the downtown network are presented in Table 3. Reservations greatly helped travel times and congestion, cutting travel times by an additional 55% at 100% demand. When combined with reduced reaction times, the total reduction in travel time was 78%. Reservations were highly effective in downtown Austin—more effective than in the freeway or arterial networks—even with the high congestion. In downtown Austin, most intersections are controlled by signals, with significant potential for improvement from reservations. Although many intersections are close together, congested intersections might be avoided by dynamic user equilibrium route choice decisions, which would avoid the issues seen with reservations in Lamar Boulevard and 38th Street. The increased capacity from 100% AVs also contributed, reducing travel times by around 51%.

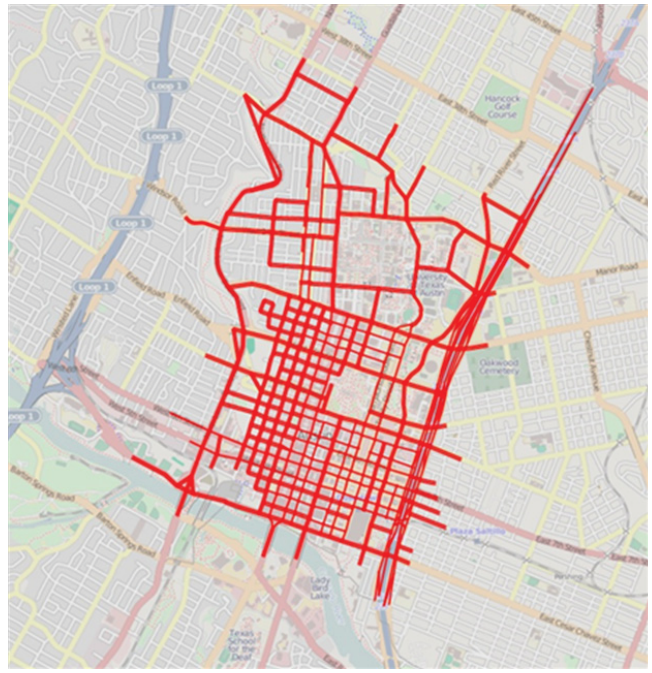


FIGURE 5 Downtown Austin network.

CONCLUSIONS

This paper is the first study that used the CTM to study the effects of reservation-based intersection control and reduced following headways for AVs on large networks. The authors studied several arterial and freeway networks that are among the 100 most congested roads

TABLE 3 Downtown Austin Results

Intersection Control	Demand (%)	Proportion of AVs	TSTT (h)	Travel Time per Vehicle (min)
Traditional	100	0	18,040.2	17.23
Traditional	100	0.25	13,371.4	12.77
Traditional	100	0.5	11,522.3	11
Traditional	100	0.75	9,905.1	9.46
Traditional	100	1	8,824.7	8.43
Reservations	100	1	3,984.3	3.8

in Texas to determine how AVs affect congestion on different types of roads. For arterial regions, reservations were beneficial in some situations but not in others. On Congress Avenue, a long arterial without progression, reservations improved travel times. However, on Lamar Boulevard and 38th Street, reservations gave greater priority to vehicles entering from local roads. Because intersections were so close together, queue spillback and greater congestion were created from the use of reservation controls. This result was because of the FCFS policy: vehicles were prioritized according to how long they had been waiting. In contrast, signals allowed more freedom in capacity allocation and were optimized to give arterials a greater share of the capacity. On freeway networks, the effects of reservations were again mixed. On US-290, which uses signals to control access, reservations were an overall improvement. In other freeway networks, reservations were worse than merges and diverges. In the downtown Austin grid network, reservations resulted in great reductions in travel times.

The negative results for FCFS reservations are surprising in view of the work of Fajardo et al. (*3*) and Li et al. (*4*). However, the major issue with FCFS reservations is that the FCFS policy allocates capacity in different proportions and at different times than signals. On arterials, in high demand this allocation resulted in greater capacity being given to local or collector roads. Furthermore, the lack of consistent timing for reservations disrupted progression along arterials, increasing queues and causing queue spillback at high demand.

Overall, the authors conclude that reservations using the FCFS policy have great potential for replacing signals. However, in certain scenarios (local road and arterial intersections that are close together and at high demand), signals outperform FCFS reservations. This outcome might be improved by a reservation priority policy that is more suited for the specific intersection. However, reservations were detrimental when used in place of merges and diverges. Because merges and diverges do not require the same delays as do signals, reservations have limited ability to improve their use of capacity. Furthermore, the FCFS policy could adversely affect capacity allocation. Therefore, FCFS reservations should not be used in place of merges and diverges, but other priority policies for reservations might be considered.

The capacity increases caused by reduced reaction times improved travel times significantly on all networks. Furthermore, regardless of the intersection control, intersection bottlenecks mostly benefited from increased capacity. These capacity increases arise from permitting AVs to use computer reaction times to reduce following headways safely. Although reduced headways might be disconcerting to human drivers in a shared-road scenario, the potential benefits demonstrated here are a significant incentive.

In future work, the authors would like to develop more analytical methods to determine when reservations will provide improvements over signals, merges, and diverges. The authors would also like to study priority policies other than FCFS for reservations to optimize them for different intersections. Furthermore, reservations move vehicles more similarly to adaptive signal controls than fixed-time signals and should therefore be compared with adaptive signals. Although adaptive signals still have lost time because of clearance intervals, the differences between reservations and adaptive signals should be explored. For reduced reaction times, the authors would like to determine typical reaction times for autonomous and connected vehicles. Connected (partially automated) vehicles might require greater safety margins than do AVs but still reduce reaction times sufficiently to achieve significant improvements in capacity. Finally, more thorough analyses of how AVs affect link queues and intersection flow would be beneficial for policy on when to use reservations and how to plan for widespread use of AVs.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the support of the Data-Supported Transportation Operations and Planning Center, the National Science Foundation, and the Texas Department of Transportation.

REFERENCES

1. Dresner, K., and P. Stone. Multiagent Traffic Management: A Reservation-Based Intersection Control Mechanism. In *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems, Volume 2.* IEEE Computer Society, Washington, D.C., 2004, pp. 530–537.
2. Dresner, K., and P. Stone. Traffic Intersections of the Future. In *Proceedings of the 21st National Conference on Artificial Intelligence, Volume 2,* American Association for Artificial Intelligence, Palo Alto, Calif., 2006, pp. 1593–1596.
3. Fajardo, D., T.-C. Au, S. T. Waller, P. Stone, and D. Yang. Automated Intersection Control: Performance of Future Innovation Versus Current Traffic Signal Control. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2259,* Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 223–232.
4. Li, Z., M. V. Chitturi, D. Zheng, A. R. Bill, and D. A. Noyce. Modeling Reservation-Based Autonomous Intersection Control in VISSIM. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2381,* Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 81–90.
5. Kesting, A., M. Treiber, and D. Helbing. Enhanced Intelligent Driver Model to Access the Impact of Driving Strategies on Traffic Capacity. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* Vol. 368, No. 1928, 2010, pp. 4585–4605.
6. Shladover, S. E., D. Su, and X.-Y. Lu. Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2324,* Transportation Research Board of the National Academies, Washington, D.C., 2012, pp. 63–70.
7. Levin, M. W., and S. D. Boyles. Effects of Autonomous Vehicle Ownership on Trip, Mode, and Route Choice. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2493,* Transportation Research Board, Washington, D.C., 2015, pp. 29–38.
8. Braess, P. D. D. D. Über ein Paradoxon aus der Verkehrsplanung. *Unternehmensforschung,* Vol. 12, No. 1, 1968, pp. 258–268.
9. Daganzo, C. F. Queue Spillovers in Transportation Networks with a Route Choice. *Transportation Science,* Vol. 32, No. 1, 1998, pp. 3–11.
10. Carlino, D., M. Depinet, P. Khandelwal, and P. Stone. Approximately Orchestrated Routing and Transportation Analyzer: Large-Scale Traffic Simulation for Autonomous Vehicles. In *Proceedings of 2012 15th International IEEE Conference on Intelligent Transportation Systems (ITSC),* IEEE, New York, 2012, pp. 334–339.
11. Levin, M. W., and S. D. Boyles. Intersection Auctions and Reservation-Based Control in Dynamic Traffic Assignment. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2497,* Transportation Research Board, Washington, D.C., 2015, pp. 35–44.
12. Levin, M. W., and S. D. Boyles. A Multiclass Cell Transmission Model for Shared Human and Autonomous Vehicle Roads. *Transportation Research Part C: Emerging Technologies,* Vol. 62, 2016, pp. 103–116.
13. Daganzo, C. F. The Cell Transmission Model: A Dynamic Representation of Highway Traffic Consistent with the Hydrodynamic Theory. *Transportation Research Part B: Methodological,* Vol. 28, No. 4, 1994, pp. 269–287.
14. Daganzo, C. F. The Cell Transmission Model, Part II: Network Traffic. *Transportation Research Part B: Methodological,* Vol. 29, No. 2, 1995, pp. 79–93.

15. Dresner, K., and P. Stone. Human-Usable and Emergency Vehicle-Aware Control Policies for Autonomous Intersection Management. Presented at Fourth International Workshop on Agents in Traffic and Transportation (ATT), Hakodate, Japan, May 2006.
16. Schepperle, H., and K. Böhm. Auction-Based Traffic Management: Towards Effective Concurrent Utilization of Road Intersections. In *Proceedings of 2008 10th IEEE Conference on E-Commerce Technology and the Fifth IEEE Conference on Enterprise Computing, E-Commerce, and E-Services,* IEEE, New York, 2008, pp. 105–112.
17. Vasirani, M., and S. Ossowski. A Market-Based Approach to Accommodate User Preferences in Reservation-Based Traffic Management. Presented at 6th Workshop on Agents in Traffic and Transportation, Toronto, Ontario, Canada, 2010.
18. Carlino, D., S.D. Boyles, and P. Stone. Auction-Based Autonomous Intersection Management. In *Proceedings of the 2013 16th International IEEE Conference on Intelligent Transportation Systems (ITSC),* IEEE, New York, 2013, pp. 529–534.
19. Hausknecht, M., T.C. Au, and P. Stone. Autonomous Intersection Management: Multi-Intersection Optimization. In *Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS),* IEEE, New York, 2011, pp. 4581–4586.
20. Dresner, K.M., and P. Stone. Sharing the Road: Autonomous Vehicles Meet Human Drivers. In *IJCAI 2007, Proceedings of the 20th International Joint Conference on Artificial Intelligence,* Vol. 7, Morgan Kaufmann Publishers, San Francisco, Calif., 2007, pp. 1263–1268.
21. Bento, L., R. Parafita, S. Santos, and U. Nunes. Intelligent Traffic Management at Intersections: Legacy Mode for Vehicles Not Equipped with V2V and V2I Communications. In *Proceedings of the 2013 16th International IEEE Conference on Intelligent Transportation Systems (ITSC),* IEEE, New York, 2013, pp. 726–731.
22. Qian, X., J. Gregoire, F. Moutarde, and A. De La Fortelle. Priority-Based Coordination of Autonomous and Legacy Vehicles at Intersection. In *Proceedings of the 2014 IEEE 17th International Conference on Intelligent Transportation Systems (ITSC),* IEEE, New York, 2014, pp. 1166–1171.
23. Li, P.Y., and A. Shrivastava. Traffic Flow Stability Induced by Constant Time Headway Policy for Adaptive Cruise Control Vehicles. *Transportation Research Part C: Emerging Technologies,* Vol. 10, No. 4, 2002, pp. 275–301.
24. Schakel, W.J., B. van Arem, and B.D. Netten. Effects of Cooperative Adaptive Cruise Control on Traffic Flow Stability. In *Proceedings of the 2010 13th International IEEE Conference on Intelligent Transportation Systems (ITSC),* IEEE, New York, 2010, pp. 759–764.
25. Blumberg, M., and H. Bar-Gera. Consistent Node Arrival Order in Dynamic Network Loading Models. *Transportation Research Part B: Methodological,* Vol. 43, No. 3, 2009, pp. 285–300.
26. Johansson, G., and K. Rumar. Drivers' Brake Reaction Times. *Human Factors: The Journal of the Human Factors and Ergonomics Society,* Vol. 13, No. 1, 1971, pp. 23–27.
27. Daganzo, C.F. Queue Spillovers in Transportation Networks with a Route Choice. *Transportation Science,* Vol. 32, No. 1, 1998, pp. 3–11.

The Standing Committee on Traffic Flow Theory and Characteristics peer-reviewed this paper.