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# Autonomous cars: The tension between occupant experience and intersection capacity

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ABSTRACT

Systems that enable high levels of vehicle-automation are now beginning to enter the commercial marketplace. Road vehicles capable of operating independently of real-time human control under an increasing set of circumstances will likely become more widely available in the near future. Such vehicles are expected to bring a variety of benefits. Two such anticipated advantages (relative to human-driver vehicle control) are said to be increased road network capacity and the freeing up of the driver-occupant's time to engage in their choice of leisurely or economically-productive (non-driving) tasks.

In this study we investigate the implications for intersection capacity and level-of-service of providing occupants of *automated* (without real-time human control), *autonomously-operating* (without vehicle-to-X communication) cars with ride quality that is equivalent (in terms of maximum rates of longitudinal and lateral acceleration) to two types of rail systems: [urban] light rail transit and [inter-urban] high-speed rail. The literature suggests that car passengers start experiencing discomfort at lower rates of acceleration than car drivers; it is therefore plausible that occupants of an autonomously-operating vehicle may wish to instruct their vehicle to maneuver in a way that provides them greater ride comfort than if the vehicle-control algorithm simply mimicked human-driving-operation.

On the basis of traffic microsimulation analysis, we found that restricting the dynamics of autonomous cars to the acceleration/deceleration characteristics of both rail systems leads to reductions in a signalized intersection's vehicle-processing capacity and increases in delay. The impacts were found to be larger when constraining the autonomous cars' dynamics to the more-restrictive acceleration/deceleration profile of high-speed rail. The scenarios we analyzed must be viewed as boundary conditions, because autonomous cars' dynamics were by definition never allowed to exceed the acceleration/deceleration constraints of the rail systems. Appropriate evidence regarding motorists' preferences does not exist at present; establishing these preferences is an important item for the future research agenda.

This paper concludes with a brief discussion of research needs to advance this line of inquiry.



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## 1. Introduction

Vehicle automation is rapidly rising up the agenda of the automotive sector; new cars increasingly contain systems that enable high levels of partial-automation (cf. US NHTSA (2013) for widely-recognized definitions of vehicle automation levels). There is also growing interest in the impacts on road network operations among transportation planners and road network managers.

Many observers speculate that two of the benefits of road vehicle automation will be (1) increased road network capacity (Li et al., 2013; Shladover, 2009; Ge and Orosz, 2014; Zohdy et al., 2014; Kesting et al., 2008; Fagnant and Kockelman, 2014), and (2) freeing up of the occupant's in-car time for a range of leisurely and economically-productive activities that are either not possible at all while one is driving, or are not as productive while driving because the driver must continuously devote a share of his/her cognitive resources to driving-related tasks (Smith, 2012; Speiser et al., 2014; Anderson et al., 2014; Preimus and Van Wee, 2013). Bhat and Howard (2014), for instance, ask: "*Will autonomous vehicles reduce roadway congestion and expand people's willingness to be in a car through reduced stress* <u>*and*</u> *ability to do other tasks, thereby increasing commute-sheds and lengthening trips?*" [underlining added].

Rail is widely described as being particularly well suited to leisurely or productive activities, as passengers are fully disengaged from vehicle operation (aside from the requirement for enough situational awareness that they exit the train at their desired station) (Halden, 2003; FIckling et al., 2009; Lyons and Urry, 2005; Lyons et al., 2007; Pawlak et al., 2012; Thalys, 2012). As is discussed in detail in Section 3, passengers on certain types of trains are also subject to smoother acceleration/deceleration profiles than car occupants. The smoother ride experienced by the passenger further enables leisurely or productive tasks. This is consistent with earlier work that suggests that car *passengers* (who can engage in leisurely or productive tasks that cannot be performed while driving) begin to experience discomfort at lower rates of acceleration than car *drivers* do (Tan, 2005; Fitzpatrick et al., 2007).

This paper investigates the impact on intersection capacity and level-of-service if autonomous cars are instructed by their occupants to travel subject to the maximum rates of longitudinal and lateral acceleration/deceleration experienced by rail passengers. The logic is that autonomous car occupants engaged in leisurely or productive activities are likely to be functionally more similar to 'car passengers' than 'car drivers'. We considered two quite distinct types of rail systems: [intra-urban] light rail transit (LRT) and [inter-urban] high-speed rail (HSR). HSR systems in many cases cater to business travelers, and provide passengers with a smoother ride quality than LRT systems do. We selected these two forms of rail travel in the interest of modeling diversity in ride quality.

The scenarios we analyzed must be viewed as boundary conditions, because autonomous cars' dynamics were by definition never allowed to exceed the acceleration/deceleration constraints of the rail systems. Appropriate evidence regarding motorists' relative preferences for ride quality, speed, and network capacity in the context of autonomous operation does not exist at present; establishing these preferences is an important item for the future research agenda.

The context of this analysis is the urban arterial street network, rather than freeway (uninterrupted-flow) conditions. Where it was necessary to draw on technical standards we did so from the state of California as described below; in California the majority (57%) of vehicle-miles of travel on public roads occur on the arterial (non-freeway) network (CalTrans, 2013). Using traffic microsimulation techniques, we evaluate a relatively near-term context characterized by:

- Mixed traffic streams (on a signalized urban arterial network) consisting of both human-driven cars and autonomously-operating cars which do not require continuous monitoring by the cars' occupant. Platooning does not take place; inter-vehicle headways between autonomous cars and the vehicles in front of them are equal to (or larger in certain scenarios, as described in Section 3) those of human-driven cars.
- No vehicle-to-X (vehicle-to-vehicle, vehicle-to-infrastructure, etc.) communications. Such communications capabilities enable cooperative behavior, but also introduce complexities (including novel types of liability in case of a mishap) and are therefore not in general present in the first generation of commercially-available driver-assist autonomous-operation systems (e.g. the systems available on the 2014 Mercedes S-Class, cf. Mercedes-Benz, 2014).

The findings of this analysis highlight the trade-offs between ride quality in autonomous cars and intersection capacity. Since it appears that car drivers and car passengers experience ride comfort differently (due to the driver being necessarily engaged in the driving task) (Tan, 2005; Fitzpatrick et al., 2007), it is plausible that autonomous car occupants wishing to engage in novel types of in-car leisurely or economically-productive tasks may wish to trade off between their ride comfort and travel time in different ways than car drivers do. The tension highlighted in this paper is a special case of the generic characteristic of congestible transportation networks that private costs/benefits and social costs/benefits are in general not perfectly aligned. The general notion that travelers seek comfort (which comprises multiple dimensions, including ride quality) in addition to seeking to minimize their travel time is uncontroversial (Jain and Lyons, 2008; Ortuzar and WIllumsen, 2011); if comfort were irrelevant to people's transport choices no person would walk anywhere: such trips would instead all be made at full sprinting pace.

These findings represent an important and timely contribution to the literature, as the tension analyzed here is not typically taken into account in planning for vehicle automation. For instance, Gucwa (2014) recently presented results of a first-of-its-kind activity-based analysis of the prospective impacts of road vehicle automation on travel patterns in the

**Table 1**
Maximum typical rates of acceleration and deceleration during revenue service for light rail and high-speed rail. *Source:* Light rail (Parsons Brinckerhoff, 2012); high-speed rail (CA HSR Authority, 2004, 2009).

| | Light rail transit | High-speed rail |
|---|---|---|
| Longitudinal acceleration | 1.34 m/s$^2$ (3 miles-per-hour/s) | 0.58 m/s$^2$ (1.3 miles-per-hour/s) |
| Longitudinal deceleration | −1.34 m/s$^2$ (3 miles-per-hour/s) | −0.54 m/s$^2$ (−1.2 miles-per-hour/s) |
| Lateral acceleration | 0.98–1.47 m/s$^2$ (0.1–0.15 g; the less-comfortable of these two values [0.15 g] was used in the present study) | 0.49 m/s$^2$ (0.05 g) |

Note: 'g' represents the standard value of gravity on the earth's surface, equal to approximately 9.8 m/s$^2$.

San Francisco Bay Area, with the objective of identifying autonomous cars' system-level impacts. The study was based on assumptions that road capacity on all road-network segments would remain constant or increase (0%, +10%, or +100%) and that in-vehicle travel time would *simultaneously* be either unchanged or less burdensome (through a reduction in the disutility of travel, known as the *value of time*, to ½ of the current value of in-car travel time in one scenario, and to the [lower] current value-of-time on "*high-quality rail services*" in another scenario). In no scenario was a conflicting relationship between capacity and value-of-time analyzed. Gucwa's findings suggest a short-run increase of 4–8% in vehicle-miles of travel.

The remainder of this paper is organized as follows: Section 2 discusses background to the present study and Section 3 describes the methods and data we employed. Section 4 then presents and discusses the quantitative results. Section 5 concludes the paper with a summary of findings and a discussion of future research needs for this line of inquiry.

## 2. Background

As interest in automated operation of road vehicles has increased in recent years, the possibility it opens up for car occupants to engage in novel types of leisurely or economically-productive tasks while traveling by car has been a frequently-identified large-scale benefit (Smith, 2012; Speiser et al., 2014; Anderson et al., 2014; Preimus and Van Wee, 2013). The scholarly discourse has also identified potentially-large increases in road capacity that may arise from vehicle automation. Capacity increases have typically been analyzed in two contexts: *mainline* freeway segments where the reduced reaction time of autonomously-operating cars can in principle allow shorter inter-vehicle headways, and arterial-network intersections where vehicle-to-vehicle and/or vehicle-to-infrastructure communications flexibly allocate priority in real-time and therefore eliminate the need for a traditional traffic signal (Li et al., 2013; Shladover, 2009; Ge and Orosz, 2014; Zohdy and Rakha, forthcoming; Kesting et al., 2008; Fagnant and Kockelman, 2014).

A notable exception to this is work by Smith (2012), who discusses the possibility of road capacity being reduced if autonomously-operating cars are programmed to operate at 'safe' three-second headways,[3] in contrast to the actual 1.5 s headways implied by the 2400 vehicles/h theoretical capacity of a freeway lane under optimal conditions. Smith also suggests that autonomous cars may well proceed more tentatively after coming to a stop than human drivers (on average) do, and may also stop more frequently for pedestrians. Of further interest, Hamish Jamson et al. (2013) employed a driving simulator to identify the types of activities that autonomously-operating cars' occupants would perform. In their research design, Jamson and colleagues analyzed an autonomous-operation concept on a freeway in which the occupant needed to manually disengage the system to change lanes to pass a slower-moving vehicle in front. The authors did not study the relationship with road capacity, but intriguingly Jamson et al. reported that participants in their experiment chose to experience lower average travel speeds in the 'with-automation' scenario versus a control scenario with only manual driving. The present study builds on the existing literature in mapping the relationship between road network *capacity* and the *comfort* of the autonomous-vehicle occupant(s).

Traveler *comfort* is a subjective concept, with seminal studies in the domain dating from the 1970s (Hoberock, 1976; Jacobsen et al., 1978; McKenzie and Brumaghin, 1976). Certain correlates of experienced comfort are clear: Temperature, rate of acceleration/deceleration, 'jerk' (the first derivative of acceleration), seating type, perceived personal security, crowding level, etc. Even if only rail vehicles and only quantitative criteria associated with the rail vehicle's movement are considered, there is no single universally-accepted set of passenger comfort criteria (Kilinc and Baybura, 2012; Persson, 2008). For the purposes of this analysis, we considered two types of rail services – light rail transit (LRT) and high-speed rail (HSR) – and maximum rates of acceleration/deceleration in the lateral and longitudinal dimensions as the passenger-comfort criteria. Table 1 shows the maximum rates of acceleration/deceleration used in the present study for LRT and HSR; the LRT criteria are sourced from U.S. national guidance (Parsons Brinckerhoff, 2012) and the HSR criteria are based on California's prospective HSR network (CA HSR Authority, 2004, 2009). The upper-boundary levels of acceleration in both the longitudinal and lateral dimensions are smaller for HSR than LRT; HSR's relatively-smooth acceleration/deceleration profile enables activities such as dining experiences where a drink can be consumed without the need for a restraint and/or a lid to prevent splashing (SNCF, 2014).

[3] Maintaining a following distance of at least three seconds is the guidance that drivers are given regarding safe driving behavior (cf. CA Department of Motor Vehicles, 2011).

**Table 2**
Analysis of US EPA's standard 'city' and 'highway' light-duty vehicle drive cycles with respect to HSR and LRT maximum rates of acceleration (respectively: deceleration). *Source:* Authors' analysis of speed profiles (at 10-Hz frequency) of US EPA's *Urban Dynamometer Driving Schedule* ('City') and *Highway Fuel Economy Driving Schedule* ('Highway') (US EPA, 2014).

| | *Urban Dynamometer Driving Schedule* (a.k.a. 'City test') | *Highway Fuel Economy Test Driving Schedule* (a.k.a. 'Highway test') |
|---|---|---|
| Maximum rate of acceleration (respectively: deceleration) | 1.5 $m/s^2$ (−1.5 $m/s^2$) | 1.4 $m/s^2$ (−1.5 $m/s^2$) |
| Proportion of drive cycle during which vehicle accelerates in excess of maximum acceleration rate of *light rail transit* (1.34 $m/s^2$) | 4.5% | 0.4% |
| Proportion of drive cycle during which vehicle decelerates in excess of maximum deceleration rate of *light rail transit* (−1.34 $m/s^2$) | 6.4% | 0.7% |
| Number of discrete occurrences during drive cycle that vehicle accelerates in excess of maximum acceleration rate of *light rail transit* (1.34 $m/s^2$) | 17 (average occurrence: once per 81 s) | 1 occurrence during the 22:49 (minutes:seconds) drive cycle |
| Number of discrete occurrences during drive cycle that vehicle decelerates in excess of maximum deceleration rate of *light rail transit* (−1.34 $m/s^2$) | 24 (average occurrence: once per 57 s) | 2 (average occurrence: once per 11:24 [minutes:seconds]) |
| Proportion of drive cycle during which vehicle accelerates in excess of maximum acceleration rate of *high-speed rail* (0.58 $m/s^2$) | 13.2% | 2.1% |
| Proportion of drive cycle during which vehicle decelerates in excess of maximum deceleration rate of *high-speed rail* (−0.54 $m/s^2$) | 13.6% | 3.8% |
| Number of discrete occurrences during drive cycle that vehicle accelerates in excess of maximum acceleration rate of *high-speed rail* (0.58 $m/s^2$) | 44 (average occurrence: once per 31 s) | 2 (average occurrence: once per 11:24 [minutes:seconds]) |
| Number of discrete occurrences during drive cycle that vehicle decelerates in excess of maximum deceleration rate of *high-speed rail* (−0.54 $m/s^2$) | 31 (average occurrence: once per 44 s) | 5 (average occurrence: once per 4:34 [minutes:seconds]) |

An important issue is whether or not human-driven cars operate within the LRT and HSR vehicle-dynamics constraints. Human driver behavior is a complex topic and there is much heterogeneity between drivers; for the purposes of this analysis we evaluated the U.S. *Environmental Protection Agency's* standard 'City' and 'Highway' drive cycles used to benchmark light-duty vehicles' fuel economy with respect to the LRT and HRT criteria (US EPA, 2014). Both drive cycles are published as speed profiles at 10-Hz temporal resolution. The speed profiles were converted into [longitudinal] acceleration/deceleration profiles, against which the LRT and HSR maximum rates were compared. As can be seen in Table 2, *both* of the standard drive cycles exceed *both* the maximum acceleration and deceleration rates for *both* the LRT and HSR criteria. For instance, in the 'City test' drive cycle the vehicle accelerates in excess of the HSR criteria (0.58 $m/s^2$) 44 times, for an average occurrence of once every 31 s.

The kinematics of autonomous vehicles are likely to differ from human-driven vehicles due to the differences in perception, information processing, decision-making and actuation capabilities of humans and machines (Frazzoli, 2001; Levinson, 2011; Stavens, 2012). To the authors' knowledge, however, the relationship between the kinematics of an autonomously-operating vehicle and the in-vehicle experience of its occupant(s) has yet to be investigated.

## 3. Methods

This section describes the traffic microsimulation techniques we employed (using VISSIM software, PTV (2012)) to assess the hypothesized relationship between intersection capacity and the occupants' ride experience in autonomous cars. While this study's original contribution is the exposition of the linkage between autonomous cars' effects on capacity and their occupants' comfort and use of time while traveling, we note that there is an emerging body of research using traffic microsimulation techniques to analyse autonomous vehicles' operations (Li et al., 2013; Miles, 2014).

### 3.1. Generic simulation parameters

We first defined the geometry and traffic demand of a schematic signalized intersection to be used in this analysis. We elected to design a road network consisting of a single four-way 90° signalized intersection with identical single-lane approaches on all four legs (Fig. 1 shows schematic intersection geometry). All traffic lanes were defined to be 12 feet in width. We did not explicitly account for the vertical dimension (e.g. the crown of a road's centerline) or random vibration in any of the three dimensions (longitudinal/lateral/vertical); the road surface was assumed to be perfectly flat and the effects of vehicles' suspensions were also not explicitly modeled. Therefore, longitudinal and lateral acceleration (excepting random vibration) represent vehicle occupants' ride experience as modeled in this analysis.

Curb radii connecting the curblines of adjacent intersection legs were defined to be 30 feet; the AASHTO Green Book notes that "Guidelines for right-turning radii into minor side streets in urban areas usually range from 1.5 to 9 m [5 to 30 ft]" (AASHTO, 2011, pp. 9–92). We selected the upper limit of curb radii as a conservative value; tighter-radii curbs would necessitate smaller-radius right- and left-turning movements which would further increase the impacts of the lateral acceleration constraints. Fixed-radius curves were connected directly to tangent sections; spiral transition curves were not modeled. This treatment is conservative, as the use of spiral curves to connect perpendicular lines necessitates a variable-radius curve with

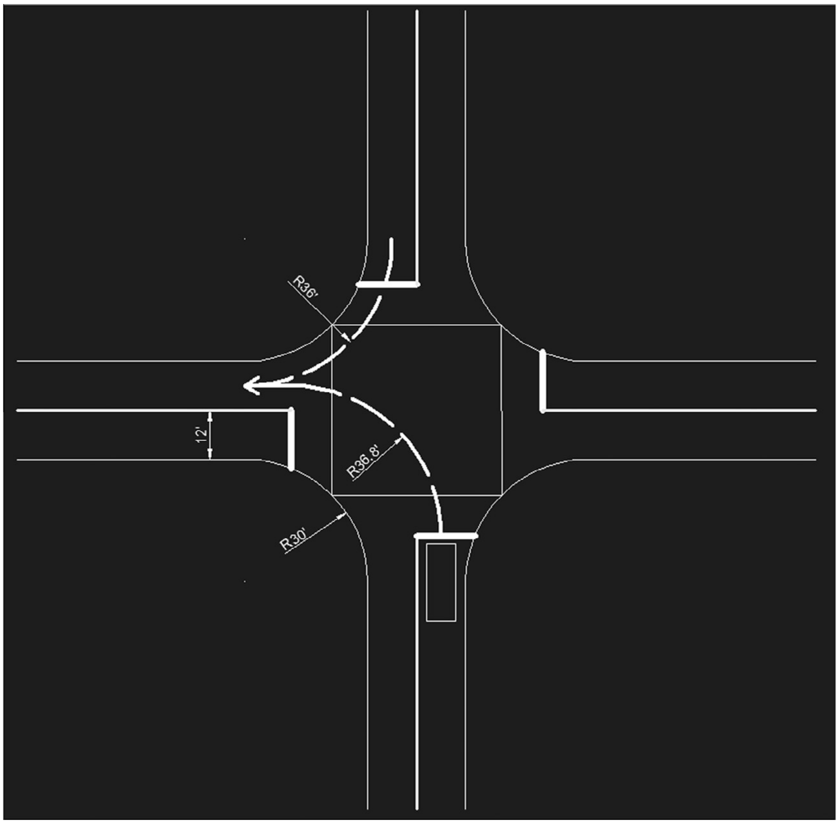


**Fig. 1.** Drawing of schematic intersection geometry analyzed in traffic microsimulation. *Source:* Authors' own.

a smaller minimum radius than if the same two perpendicular lines are connected by a fixed-radius curve (i.e. spiral curves mitigate lateral jerk rather than acceleration).

Stop bars on all intersection approaches were located 10 feet in advance of the intersection 'box' (the box was defined by the square connecting the mid-points of the curb curves). The 10-feet dimension is based on the presence of a 6 feet wide crosswalk and 4 feet wide gap between the crosswalk and stop-line.[4] Based on this geometry, the turning radius (defined for the centerline of the vehicle, midway between the 'driver' and 'passenger' seats) of left-turning vehicles was marginally larger than the corresponding turning radius for right-turning vehicles (36.8 feet versus 36.0 feet, respectively, as shown in Fig. 1).

Free-flow speed was defined as 50 km/h on all intersection legs. VISSIM does not automatically calculate vehicles' turning speeds as a function of turning radius; the user must manually input turning speeds. California's *Highway Design Manual* (CalTrans, 2014) defines 'comfortable' longitudinal speed as a function of horizontal curvature for curves larger than 130 feet in radius (this corresponds to a 'comfortable' speed of 20 miles per hour). We plotted best-fit linear, exponential, and power-function curves through 'comfortable' speeds of 20, 30, 40, and 50 miles per hour; empirically the best fit ($r^2 = 0.9999$) was found to be a power-function curve (see Fig. 2). We then extrapolated this relationship to horizontal curve radii of 36.0 and 36.8 feet (right and left turning traffic, respectively), and calculated 'comfortable' turning speeds of human-driven cars to be 10.7 mph (17.2 km/h) and 10.8 mph (17.3 km/h), for right- and left-turning vehicles, respectively.

Signal timing in all scenarios was based on a 90-s cycle length in two-phase operation with permissive left turns. In the Baseline scenario, the yellow interval was set at 3 s, the value recommended by the *Institute of Transportation Engineers* (ITE) for a free-flow speed of 50 km/h (Table 17.1 in Roess et al. (2004)). The all-red clearance time was set to 2 s (following equation 17-2c in Roess et al. (2004)), in order to allow a vehicle whose front bumper passes the stop bar at the end of the yellow interval to travel completely through the intersection, including the opposite crosswalk, before the beginning of the conflicting signal phase (based on a speed of 50 km/h and a distance of 22 m to be traveled).

Traffic demands on all four approaches were defined to be identical with a ratio of 1:3:1 between left-turning, through, and right-turning traffic, respectively, with the traffic streams consisting exclusively of passenger cars (i.e. no heavy vehicles, in the interest of simplicity). After subtracting the required yellow and all-red intervals, a total of 80 s is left for green intervals, which was allocated half (40 s) to north–south traffic and half to east–west traffic, as traffic demands were equal on all approaches.

[4] These are the minimum values per the Manual on Uniform Traffic Control Devices (MUTCD) (USDOT, 2012).

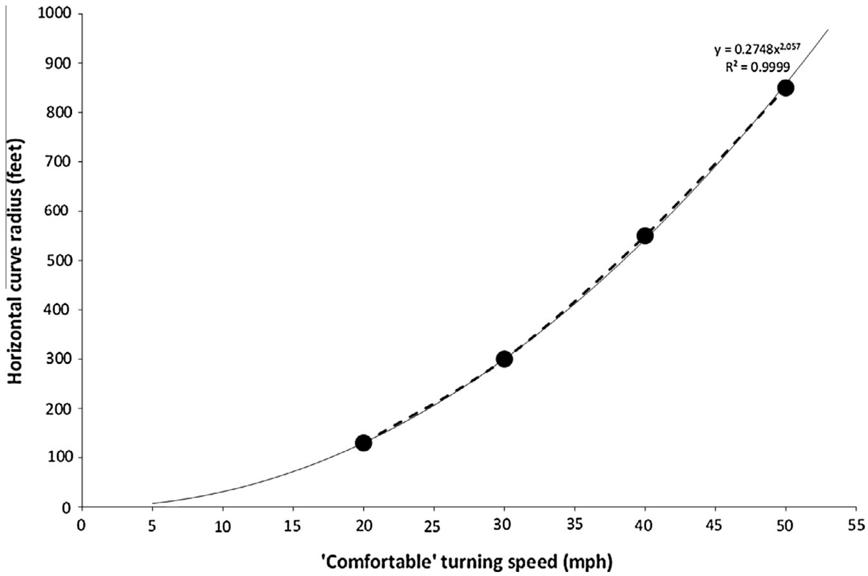


**Fig. 2.** Plot of horizontal curve radius versus 'comfortable' turning speed (circle markers connected by dashed line), and curve of best-fit power function with extrapolation above and below (thin solid line). *Source:* Authors' extrapolation of values in Table 203.2 of CalTrans Highway Design Manual, Chapter 200: Geometric Design and Structure Standards (CalTrans, 2014).

Right turns on red were allowed. No pedestrian activity was modeled; the analysis focused exclusively on vehicular traffic. For the purposes of estimating average free-flow delay per vehicle, undersaturated traffic demand was set at 250 vehicles/h on each approach, which yielded an average free-flow delay (due to signal control) of 20.0 s/vehicle in the baseline scenario (the boundary between levels-of-service 'B' and 'C' for signalized intersections, as defined by the *Highway Capacity Manual* (TRB, 2010)). A single-intersection network allows intersection capacity to be defined as the observed traffic throughput (aggregated across all approaches) under oversaturated demand conditions (there is no blocking, starvation or other interaction between traffic operations at adjacent intersections). For the purposes of estimating intersection capacity, oversaturated traffic demand was set at 2000 vehicles/h on each approach. In the baseline scenario, average intersection capacity was found to be 1793 vehicles/h.

Except as described otherwise in this section, VISSIM's default values for all simulation parameters were used. For reference, Fig. 3 shows the parameters of the default distributions in VISSIM for passenger cars' longitudinal acceleration and deceleration values.

With the exception of Scenario #1 (the Baseline scenario, in which the traffic stream was 100% human-driven cars), in all scenarios described below the traffic stream was defined to be 75% human-driven cars and 25% autonomously-operating cars. An important characteristic of this analysis is that we did not model any sort of automated-vehicle platooning (i.e. reduced inter-vehicle headways in comparison to human drivers) or other behavior enabled by autonomous cars' reduced reaction times and the unique ways (relative to human drivers) that they respond to external stimuli. VISSIM does not explicitly model drivers' reaction times (the simulation time step is implicitly used as the reaction time); this is a general limitation of traffic simulation models, as shown recently by Basak et al. (2013); the authors report that "*the implementation of reaction time in traffic simulation models is limited, and in many cases derives its characteristics more from computational convenience and less from behavioral theory*".

All simulations included a 15-min 'warm-up' increment when no statistics were recorded, followed by a 60-min analysis period. To accommodate the stochastic nature of traffic microsimulation, 100 runs of each scenario were performed (each with a unique 'seed' value) for input into the statistical analysis of the outputs (delay per vehicle and intersection capacity). The remainder of this section describes the scenarios analyzed in this study, which are summarized in Tables 3 and 4 for constraints on autonomous-car dynamics consistent with LRT and HSR, respectively.

### *3.2. LRT/HSR Scenario #2: longitudinal and lateral acceleration/deceleration constraints, with signal timing not modified*

In 'LRT Scenario #2' autonomous cars were constrained to the maximum acceleration/deceleration values of LRT (in both the *longitudinal* and *lateral* dimensions), and likewise for 'HSR Scenario #2'. Signal timing was unchanged from the baseline scenario (Scenario #1). It must be noted that acceleration/deceleration (the 2nd derivative of distance with respect to time) is only one dimension of passengers' ride experience, others include vibration/oscillation (which depends in part on a vehicle's suspension) and 'jerk' (the 3rd derivative of distance with respect to time; the rate of change in acceleration/deceleration). 'Jerk' is known to be an important determinant of passenger comfort (Hoberock, 1976; Jacobsen et al., 1978;

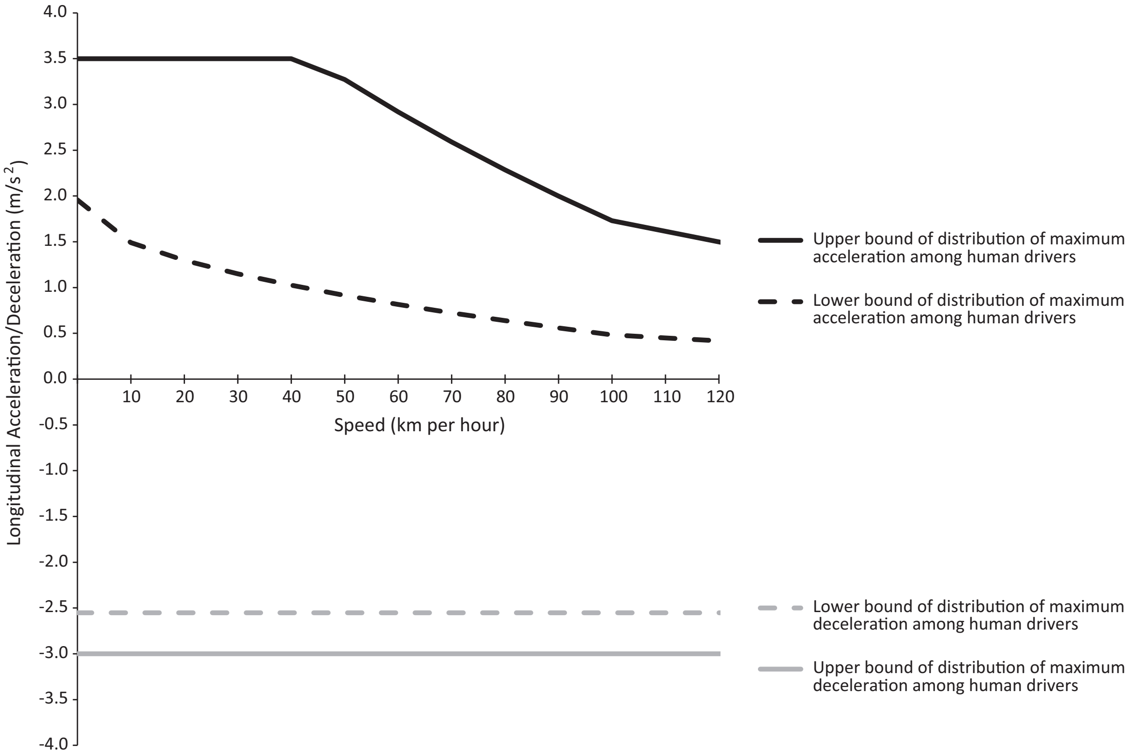


**Fig. 3.** VISSIM's default distribution of maximum longitudinal acceleration/deceleration for passenger cars. *Source:* Plot prepared by authors. VISSIM's distributional parameters sourced from (PTV, 2012).

McKenzie and Brumaghin, 1976); however, unlike acceleration, 'jerk' is not user-definable in VISSIM simulation software. It is also worth noting that point values were used for the HSR and LRT constraints (i.e. all autonomous cars in the simulation were subject to the same acceleration/deceleration constraints); by contrast human-driver behavior is heterogeneous (this is taken into account in VISSIM via standard distributions from which each human-driven car's maximum rate of acceleration and deceleration is randomly drawn; see Fig. 3).

The combination of low rates of maximum deceleration and the short duration of the signal phases' yellow interval (3 s) means that autonomous cars must slow to 29 km/h or 12 km/h (in the LRT Scenario #2 and HSR Scenario #2, respectively). The standard calculation of the duration of a signal phase's *yellow* interval is based on allowing a vehicle (traveling at the road's free-flow speed) that approaches the intersection at the point in time when a green interval transitions to a yellow interval to decelerate to a complete stop before reaching the stop-line (Eq. (18.2) of Roess et al., 2004). The values of 29 km/h (LRT) and 12 km/h (HSR) are calculated from the maximum deceleration values for LRT and HSR (1.34 $m/s^2$ and 0.54 $m/s^2$, respectively) and the known 3-s duration of the yellow interval in this scenario. This is because an autonomously-operating car (as defined for the purposes of this analysis: without V2X communication) approaching the intersection during a green interval does not know when the signal will transition to the yellow interval, and if that happens the vehicle must be able to either decelerate to a stop before the stop-line or to accelerate and completely traverse the intersection before conflicting traffic receives a green interval. If the vehicle does not do either of these maneuvers it is defined by traffic engineers as being in the *dilemma zone*, an unsafe condition (Roess et al., 2004).

In order to operate within the relevant maximum rate of lateral acceleration (either LRT or HSR), right-turning autonomous cars are restricted to a maximum turning speed of 14.5 km/h (LRT) and 8.3 km/h (HSR) and left-turning autonomous cars are restricted to a maximum turning speed of 14.7 km/h (LRT) and 8.4 km/h (HSR).

### *3.3. LRT/HSR Scenario #3: longitudinal and lateral acceleration/deceleration constraints, with signal timing modified*

In Scenario #2, the traffic signal's timing plan was not changed but the autonomous cars were made to travel slowly in order to avoid being caught in the 'dilemma zone' at the end of signal phase. By way of contrast, in Scenarios #3, 4, and 5 the free-flow speed of the autonomous cars was defined to be the same as the human-driven vehicles (50 km/h), but the yellow and all-red intervals of the traffic signal were adjusted to accommodate their deceleration constraints. The constraints on vehicle dynamics in LRT/HSR Scenario #3 are identical in other respects to those in LRT/HSR Scenario #2.

**Table 3**
Scenarios with constraints on autonomous cars' dynamics based on maximum acceleration/deceleration rates experienced by *light rail transit* passengers. *Source:* Authors' own.

| | Signal timing | Composition of traffic stream | Free-flow speed at stop line of intersection approach | Maximum rate of longitudinal acceleration | Maximum rate of longitudinal deceleration | Right-turn turning speed | Left-turn turning speed |
|---|---|---|---|---|---|---|---|
| Baseline (Scenario #1) | Green: 40 s, Yellow: 3 s, All-red: 2 s | 100% human-driven | 50 km/h | VISSIM's default distribution of human-driver longitudinal acceleration | VISSIM's default distribution of human-driver longitudinal deceleration | 17.2 km/h | 17.3 km/h |
| LRT Scenario #2 | G: 40 s, Y: 3 s, AR: 2 s | 75% human-driven, 25% autonomous | Human-driven: 50 km/h<br>Autonomous cars: 29 km/h | Human-driven cars: same as baseline<br>Autonomous cars: 1.34 m/s$^2$ | Human-driven cars: same as baseline<br>Autonomous cars: 1.34 m/s$^2$ | Human-driven cars: 17.2 km/h<br>Autonomous cars: 14.5 km/h | Human-driven cars: 17.3 km/h<br>Autonomous cars: 14.7 km/h |
| LRT Scenario #3 | G: 35 s, Y: 5 s, AR: 5 s | 75% human-driven, 25% autonomous | 50 km/h | Human-driven cars: same as baseline<br>Autonomous cars: 1.34 m/s$^2$ | Human-driven cars: same as baseline<br>Autonomous cars: 1.34 m/s$^2$ | Human-driven cars: 17.2 km/h<br>Autonomous cars: 14.5 km/h | Human-driven cars: 17.3 km/h<br>Autonomous cars: 14.7 km/h |
| LRT Scenario #4 | G: 37 s, Y: 3 s, AR: 5 s | 75% human-driven, 25% autonomous | 50 km/h | VISSIM's default distribution of human-driver longitudinal acceleration | VISSIM's default distribution of human-driver longitudinal deceleration | Human-driven cars: 17.2 km/h<br>Autonomous cars: 14.5 km/h | Human-driven cars: 17.3 km/h<br>Autonomous cars: 14.7 km/h |
| LRT Scenario #5 | G: 38 s, Y: 5 s, AR: 2 s | 75% human-driven, 25% autonomous | 50 km/h | Human-driven cars: Same as Baseline<br>Autonomous cars: 1.34 m/s$^2$ | Human-driven cars: Same as Baseline<br>Autonomous cars: 1.34 m/s$^2$ | 17.2 km/h | 17.3 km/h |

**Table 4**
Scenarios with constraints on autonomous cars' dynamics based on maximum acceleration/deceleration rates experienced by *high-speed rail* passengers. *Source:* Authors' own.

| | Signal timing | Composition of traffic stream | Free-flow speed at stop line of intersection approach | Maximum rate of longitudinal acceleration | Maximum rate of longitudinal deceleration | Right-turn turning speed | Left-turn turning speed |
|---|---|---|---|---|---|---|---|
| Baseline (Scenario #1) | See corresponding row in Table 3 | | | | | | |
| HSR Scenario #2 | G: 40 s, Y: 3 s, AR: 2 s | 75% human-driven, 25% autonomous | Human-driven: 50 km/h<br><br>Autonomous cars: 12 km/h | Human-driven cars: same as baseline<br>Autonomous cars: 0.58 m/s$^2$ | Human-driven cars: same as baseline<br>Autonomous cars: 0.54 m/s$^2$ | Human-driven cars: 17.2 km/h<br><br>Autonomous cars: 8.3 km/h | Human-driven cars: 17.2 km/h<br><br>Autonomous cars: 8.4 km/h |
| HSR Scenario #3 | G: 23 s, Y: 12 s, AR: 10 s | 75% human-driven, 25% autonomous | 50 km/h | Human-driven cars: same as baseline<br>Autonomous cars: 0.58 m/s$^2$ | Human-driven cars: same as baseline<br>Autonomous cars: 0.54 m/s$^2$ | Human-driven cars: 17.2 km/h<br><br>Autonomous cars: 8.3 km/h | Human-driven cars: 17.3 km/h<br><br>Autonomous cars: 8.4 km/h |
| HSR Scenario #4 | G: 32 s, Y: 3 s, AR: 10 s | 75% human-driven, 25% autonomous | 50 km/h | Both human-driven cars and autonomous cars follow VISSIM's default distribution of human-driver longitudinal acceleration | Both human-driven cars and autonomous cars follow VISSIM's default distribution of human-driver longitudinal deceleration | Human-driven cars: 17.2 km/h<br>Autonomous cars: 8.3 km/h | Human-driven cars: 17.3 km/h<br>Autonomous cars: 8.4 km/h |
| HSR Scenario #5 | G: 31 s, Y: 12 s, AR: 2 s | 75% human-driven, 25% autonomous | 50 km/h | Human-driven cars: Same as Baseline<br>Autonomous cars: 0.58 m/s$^2$ | Human-driven cars: Same as Baseline<br>Autonomous cars: 0.54 m/s$^2$ | 17.2 km/h | 17.3 km/h |

Following the standard calculation of the duration of a signal phase's *yellow* interval (Eq. (18.2) in Roess et al., 2004; see the discussion in Section 3.3), the combination of the maximum rates of deceleration of LRT and HSR and a 50 km/h free-flow speed dictate that the duration of the yellow intervals must increase from 3 s to 5 s (LRT) and 12 s (HSR). In this study we analyse a context where there is no vehicle-to-infrastructure communication. Such communication could reduce or eliminate the need for extended yellow intervals, if autonomous cars' vehicle-control systems were able to know in real-time when a green interval would change, in advance of it when it physically transitions to a yellow interval.

Likewise, the standard calculation of the duration of a signal phase's *all-red* interval is to allow a vehicle that enters the intersection just at the end of a yellow interval to completely traverse (i.e. its rear bumper to exit) the intersection before a conflicting traffic stream receives a green indication. The governing movement for autonomous cars is the left-turn, which is subject to speed restrictions to limit lateral acceleration, and the vehicle must travel 22 m to fully traverse the intersection.[5] The required all-red interval is 5 s (LRT) and 10 s (HSR).

After allowing for the required yellow and all-red intervals, the remaining time for each of the two green intervals (north–south and east–west) is 35 s (LRT) and 23 s (HSR).

### *3.4. LRT/HSR Scenario #4: only lateral acceleration/deceleration constraints, with signal timing modified*

LRT Scenario #4 and HSR Scenario #4 were designed to investigate the impact of restricting only *lateral* acceleration to the maximum rate of LRT and HSR, respectively. The longitudinal acceleration/deceleration profile of autonomous cars is identical to VISSIM's default values for human-driven cars (see Fig. 3). VISSIM's default values are stochastic and (in the case of acceleration) speed-dependent (PTV, 2012). Starting from a full stop, the mean rate of maximum acceleration is uniformly distributed between 2.0 $m/s^2$ and 3.5 $m/s^2$. The distribution of maximum acceleration then decreases monotonically, and at 50 km/h it is uniformly distributed between 0.9 $m/s^2$ and 3.3 $m/s^2$. The default deceleration profile does not vary with speed, and is distributed uniformly between $-2.5$ $m/s^2$ and $-3.0$ $m/s^2$.

As in Scenario #3, signal timing is adjusted to accommodate the acceleration/deceleration profile of autonomously-operating cars. Each of the two signal phases is calculated to be 37 (32) seconds of green interval, 3 (12) seconds of yellow interval, and 5 (2) seconds of all-red interval (values outside of brackets are for LRT Scenario #4; values within brackets are for HSR Scenario #4).

### *3.5. LRT/HSR Scenario #5: only longitudinal acceleration/deceleration constraints, with signal timing modified*

This scenario is the complement of Scenario #4; only the *longitudinal* acceleration/deceleration constraints are applied to autonomous cars.

The duration of each of the two signal phases in 'LRT Scenario #5' is 38 s of green interval, 5 s of yellow interval, and 2 s of all-red interval. The corresponding values for 'HSR Scenario #5' are 31, 12, and 2 s.

### *3.6. Scenarios with 'a' suffix: autonomous cars employ extended vehicle-following headways*

In all scenarios described previously in this section, it is possible that an occupant of an autonomous car may be subject to longitudinal deceleration in excess of the defined maximum rates if they are following a human-driven vehicle at a standard headway (in the range of 2 s). This would occur if the human driver of the leading vehicle decelerates at a rate that is acceptable to them but not the following autonomous-car. In this traffic microsimulation analysis, this can occur when the signal interval changes from green to yellow; the lead human-driven vehicle may choose to decelerate to a stop before reaching the stop-line, but the autonomous car that is following cannot do so without exceeding (without providing warning to its occupant(s)) the desired maximum rate of deceleration.

In order to preclude this possibility, autonomous cars subject to a low maximum rate of longitudinal deceleration must maintain a longer headway behind the vehicle that they are following. In the case of LRT deceleration constraints, an additional headway of 6 s (in addition to standard inter-vehicle headways of human-driven vehicles) is required at 50 km/h, with an additional 19 s of headway for autonomous cars that operate subject to HSR deceleration constraints.

In the results shown in Tables 5 and 6, the suffix 'a' indicates scenarios where these longer headways were taken into account and therefore occupants of the autonomously-operating cars are never required to decelerate faster than they desire, even if the vehicle they are following stops abruptly. This was done by changing the car-following model for autonomous cars from the default Wiedemann (1974) car-following model to the Wiedemann-1999 model (PTV, 2012), as the Wiedemann (1974) model does not include a relevant inter-vehicle headway parameter than can be user-modified. This analysis provides a conservative calculation of the impacts of this operating regime for two reasons. First, the additional buffer time that must be added onto inter-vehicle headways is proportionally smaller at speeds below 50 km/h. VISSIM software does not allow this parameter to vary with vehicle speed, however. Second, if an autonomous car could identify that it is following an autonomously-operating car that with a known low maximum rate of deceleration, it could in principle elim-

[5] Authors' calculation based on intersection geometry shown in Fig. 1 and the length of a passenger car design vehicle (19′), per the AASHTO *Green Book* (AASHTO, 2011).

**Table 5**
Average, standard error, and distribution of delay (s) per vehicle. *Source:* Authors' analysis of simulation outputs.

| | Average | Standard error | Percentage change relative to baseline scenario | 5th percentile | 10th percentile | 25th percentile | 50th percentile (Median) | 75th percentile | 90th percentile | 95th percentile |
|---|---|---|---|---|---|---|---|---|---|---|
| Baseline (Scenario #1) | 20.0 | 0.1 | – | 18.1 | 18.8 | 19.2 | 19.9 | 20.7 | 21.3 | 21.5 |
| LRT Scenario #2 | 20.9 | 0.1 | +4% | 18.7 | 19.5 | 20.1 | 20.8 | 21.6 | 22.2 | 22.7 |
| LRT Scenario #2a | 23.0 | 0.2 | +15% | 20.4 | 20.8 | 21.9 | 22.8 | 23.6 | 24.9 | 25.6 |
| LRT Scenario #3 | 26.6 | 0.2 | +33% | 23.5 | 24.0 | 25.1 | 26.1 | 27.6 | 29.0 | 30.7 |
| LRT Scenario #3a | 30.0 | 0.4 | +50% | 26.1 | 26.5 | 27.9 | 29.0 | 31.2 | 33.8 | 35.7 |
| LRT Scenario #4 | 23.8 | 0.2 | +19% | 21.4 | 22.1 | 22.8 | 23.8 | 24.5 | 25.5 | 27.4 |
| LRT Scenario #4a | 27.2 | 0.3 | +36% | 23.8 | 24.3 | 25.7 | 26.8 | 28.5 | 30.0 | 35.7 |
| LRT Scenario #5 | 22.3 | 0.1 | +12% | 20.2 | 20.6 | 21.3 | 22.2 | 23.2 | 24.1 | 26.8 |
| LRT Scenario #5a | 24.9 | 0.4 | +25% | 21.9 | 22.4 | 23.3 | 24.2 | 25.5 | 26.9 | 27.5 |
| HSR Scenario #2 | 27.2 | 0.3 | +36% | 23.6 | 24.1 | 25.1 | 26.7 | 28.3 | 30.4 | 33.4 |
| HSR Scenario #2a | 43.5 | 1.0 | +118% | 32.6 | 33.8 | 38.2 | 41.0 | 46.0 | 53.6 | 59.3 |
| HSR Scenario #3 | 232.8 | 5.5 | +1064% | 149.5 | 156.1 | 183.8 | 231.1 | 286.4 | 305.7 | 318.0 |
| HSR Scenario #3a | 404.8 | 6.3 | +1924% | 289.5 | 331.6 | 353.7 | 419.3 | 449.8 | 474.6 | 493.7 |
| HSR Scenario #4 | 37.3 | 0.6 | +87% | 30.0 | 31.1 | 33.4 | 35.8 | 39.4 | 44.3 | 52.2 |
| HSR Scenario #4a | 99.7 | 3.3 | +399% | 60.2 | 66.0 | 77.7 | 90.7 | 115.7 | 158.6 | 183.3 |
| HSR Scenario #5 | 38.4 | 0.8 | +92% | 30.0 | 31.3 | 33.2 | 36.7 | 41.5 | 44.8 | 49.6 |
| HSR Scenario #5a | 86.5 | 2.9 | +333% | 54.3 | 60.8 | 67.2 | 79.3 | 94.6 | 127.4 | 137.4 |

Note: LRT: light rail transit; HSR: high-speed rail; results generated using undersaturated traffic demand (250 vehicles/h on all four approaches).

**Table 6**
Average, standard error, and distribution of intersection capacity (vehicles processed per hour, combined across all four intersection approaches). *Source:* Authors' analysis of simulation outputs.

| | Average | Standard error | Percentage change relative to baseline scenario (%) | 5th percentile | 10th percentile | 25th percentile | 50th percentile (Median) | 75th percentile | 90th percentile | 95th percentile |
|---|---|---|---|---|---|---|---|---|---|---|
| Baseline (Scenario #1) | 1793 | 1.8 | – | 1762 | 1771 | 1782 | 1790 | 1805 | 1814 | 1823 |
| LRT Scenario #2 | 1724 | 1.6 | −4 | 1697 | 1703 | 1716 | 1723 | 1735 | 1744 | 1750 |
| LRT Scenario #2a | 1585 | 2.3 | −12 | 1543 | 1555 | 1572 | 1587 | 1602 | 1614 | 1626 |
| LRT Scenario #3 | 1506 | 2.1 | −16 | 1473 | 1480 | 1492 | 1505 | 1519 | 1534 | 1547 |
| LRT Scenario #3a | 1415 | 2.4 | −21 | 1371 | 1380 | 1397 | 1417 | 1433 | 1446 | 1455 |
| LRT Scenario #4 | 1634 | 2.0 | −9 | 1596 | 1608 | 1625 | 1639 | 1654 | 1668 | 1671 |
| LRT Scenario #4a | 1483 | 2.1 | −17 | 1444 | 1460 | 1469 | 1485 | 1503 | 1523 | 1539 |
| LRT Scenario #5 | 1643 | 1.9 | −8 | 1609 | 1615 | 1631 | 1644 | 1655 | 1669 | 1673 |
| LRT Scenario #5a | 1527 | 2.2 | −15 | 1487 | 1497 | 1512 | 1528 | 1543 | 1558 | 1566 |
| HSR Scenario #2 | 1469 | 2.8 | −18 | 1418 | 1425 | 1451 | 1472 | 1489 | 1505 | 1517 |
| HSR Scenario #2a | 1259 | 2.9 | −30 | 1203 | 1216 | 1243 | 1259 | 1278 | 1295 | 1311 |
| HSR Scenario #3 | 966 | 2.2 | −46 | 932 | 936 | 950 | 963 | 978 | 995 | 1000 |
| HSR Scenario #3a | 850 | 2.4 | −53 | 811 | 817 | 833 | 850 | 866 | 881 | 888 |
| HSR Scenario #4 | 1387 | 2.4 | −23 | 1344 | 1354 | 1372 | 1388 | 1405 | 1420 | 1427 |
| HSR Scenario #4a | 1086 | 2.3 | −39 | 1046 | 1056 | 1071 | 1088 | 1102 | 1114 | 1125 |
| HSR Scenario #5 | 1293 | 2.2 | −28 | 1258 | 1264 | 1280 | 1292 | 1308 | 1320 | 1327 |
| HSR Scenario #5a | 1106 | 2.5 | −38 | 1060 | 1075 | 1089 | 1106 | 1123 | 1135 | 1141 |

Note: LRT: light rail transit; HSR: high-speed rail; results generated using oversaturated traffic demand (2000 vehicles/h on all four approaches).

inate this buffer time. VISSIM software, however, also does not allow the inter-vehicle headway parameter to vary depending on the type of vehicle that is being followed.

Tables 3 and 4 summarize the specifications of the *LRT* and *HSR* scenarios, respectively.

## 4. Results

In the Baseline scenario (with only human-driven cars), average delay per vehicle is 20 s, the boundary between level-of-service (LOS) 'B' and 'C' for a signalized intersection. Total traffic-processing capacity of the intersection is 1793 vehicles/h. (Results described in this section are found in Tables 5 and 6 for delay and capacity calculations, respectively.)

Autonomous cars are first introduced (as 25% of traffic) in Scenario #2, where signal timing is the same as in the Baseline scenario but rates of longitudinal acceleration/deceleration and lateral acceleration are constrained to the levels of LRT (in the LRT iteration of Scenario #2) or HSR (in the HSR iteration of Scenario #2). Average delay (an aggregate calculation averaged across all vehicles in the simulation: both human-driven and autonomously-operating cars) increases by 5% (LRT iteration) and 36% (HSR iteration) relative to the Baseline scenario, and capacity is correspondingly reduced by 4% (LRT) and 18%

(HSR), respectively. As would be expected, in Scenario #2 (as well as all other scenarios), the more-restrictive constraints of HSR lead to larger impacts (in terms of both delay and capacity) than the LRT constraints.

Scenario #2a is identical to Scenario #2, except that (as with all other scenarios suffixed with 'a'), autonomous cars operate at extended headways behind the car ahead of them in the traffic stream. The outcome is that autonomous cars' occupants never experience longitudinal deceleration in excess of their desired rate (either LRT or HSR), even if the car they are following suddenly decelerates without warning. In the LRT iteration of Scenario 2a, average delay per vehicle is 10% higher than in the LRT iteration of Scenario 2 and capacity is 8% lower; the corresponding numbers for the HSR iteration are larger in magnitude 60% larger delay (compared to 10%) and 14% lower capacity (compared to 8%).

In Scenario #3 signal timing is modified to account for the autonomous cars' defined operating constraints. For the LRT and HSR iterations of Scenario #3, the green interval duration is reduced by 1/8th (from 40 s to 35 s) and 43% (from 40 s to 23 s), respectively. This allows autonomous cars to travel at a higher speed as they approach the intersection. The net effects of these changes, however, are increased delay and lower capacity, when comparing the LRT and HSR iterations of Scenarios #3 and #3a to the corresponding iterations of Scenarios #2 and #2a. These effects are much larger for the HSR iterations than for the LRT iterations. For instance, the largest level of delay recorded in all scenarios of this study was in the HSR iteration of Scenario #3a, at 405 s per vehicle (well into level-of-service 'F').

The remaining sets of scenarios (#s 4/4a and 5/5a) investigate the relative contribution of the lateral (Scenarios #4 and #4a) and longitudinal (Scenarios #5 and 5a) constraints on autonomous cars' dynamics. Signal timing is adjusted in accordance with each iteration's constraints. Delay and capacity values for each of these iterations are 'worse' (higher delay and lower capacity) than the values for the Baseline scenario but 'better' than the values for the corresponding iteration of Scenarios #3 or #3a (which include operational constraints in both the longitudinal and lateral dimensions). For the LRT iterations, we found that the lateral constraints had greater impacts on both delay and capacity than the longitudinal constraints, and this was true whether or not the autonomous cars were subject to extended headways (i.e. when comparing LRT Scenario #4 to #5 and also when comparing LRT Scenario #4a to #5a). The results were mixed, however for the HSR iterations. In the HSR iterations *without* extended headways (comparing HSR Scenario #4 to #5) the longitudinal constraints had greater impacts, but in the scenarios *with the* extended headways (comparing HSR Scenario #4a to #5a) the lateral constraints had larger impacts on delay and capacity.

## 5. Conclusions

Many observers anticipate that autonomous cars will lead to travel being less burdensome on a per-minute basis (i.e. a general reduction of travelers' value-of-time, cf. (Gucwa, 2014; Bhat, 2014; Cairns et al., 2014)) due to their occupants being newly able to perform a wider range of leisure or productive activities while traveling. It is also widely anticipated that autonomous cars will, in the long run, lead to increased roadway capacity (and reduced congestion) due to shorter headways between vehicles and control of conflicting traffic streams that is more flexible than today's control options (yield-control, stop-control, traffic signals that visually convey stop/go information to drivers). Recently, for instance, Gucwa (2014) reported an in-depth analysis of the system-level impacts of autonomous vehicles, which was based on dual assumptions of *increased* road network capacity concurrent with *reduced* value-of-time due to an increased set of possible in-vehicle activities.

Car passengers can perform a greater range of leisurely and productive tasks than car drivers, and they also appear to begin to experience feelings of discomfort at lower rates of acceleration than car drivers. We therefore evaluated the implications on the capacity and level-of-service of a schematic signalized intersection of autonomous car occupants programming their cars to operate within the relatively smooth acceleration/deceleration constraints of [less-restrictive) light rail transit and (more restrictive) high-speed rail. It is worth noting that in this analysis all autonomous cars were defined to operate homogenously within the same set of constraints; in reality it may well be the case that vehicle-designers provide travelers with the opportunity to control the acceleration/deceleration profile of their vehicle as they wish, with the outcome being that some autonomous-car occupants may choose to travel at relatively smooth acceleration/deceleration profiles and others at more 'aggressive' profiles.

We wish to make clear that the authors do not take a view at the time of writing regarding the relative likelihood of each of the various scenarios that we considered, due to the absence of evidence on which to form such a judgment. As discussed below, this will depend on complex interactions between the currently-unknown preferences of individual motorists, traffic engineers, automotive designers, and vehicle regulators.

Our findings suggest a tension in the short run between these two anticipated benefits (more productive use of travel time and increased network capacity), at least in certain circumstances. It was found that the trade-off between capacity and passenger-comfort is greater if autonomous car occupants program their vehicles to keep within the constraints of HSR (in comparison to LRT). This arises because HSR's ride-experience constraints are more restrictive than LRT's. Our findings of whether maximum acceleration constraints in the longitudinal or lateral dimensions are more restrictive were different for LRT (where the lateral acceleration constraint was more restrictive in both scenarios we evaluated) and HSR (where the results were mixed in the two scenarios we studied).

The scenarios we analyzed must be viewed as boundary conditions, because autonomous cars' dynamics were by definition never allowed to exceed the acceleration/deceleration constraints of the rail systems. Appropriate evidence regarding motorists' relative preferences for ride quality, speed, and network capacity in the context of autonomous operation does not exist at present; in other words we do not know how motorists will choose to take advantage of the new capabilities offered by autonomous operation. (It is worth noting that both ride comfort and speed are experienced by the motorist himself/herself, whereas impacts on network capacity involve social costs that are imposed on *other* motorists.) In addition to not knowing how motorists will act, we also do not know how traffic engineers will respond (such as through modifying the operation of traffic signals, perhaps using strategies similar to those that we evaluated). Furthermore we do not know how the designers of autonomous-operation algorithms will make the relevant design choices, and how vehicle-operation regulators will bound these design choices. Therefore, establishing these preferences is an important item for the future research agenda; stated-preference and game-theoretic approaches may be appropriate to advance this line of inquiry. In this analysis, we neglected movement due to a vehicle's suspension (Wong, 2008). One plausible strategy to manage the tension between comfort and capacity identified in this paper would be to incorporate (subject to both economics and laws of physics) mechanisms such as those used on high-speed tilting trains more widely into road vehicle design. In principle, this could include actuators that tilt the passenger cabin of an automated car in multiple axes to counteract the degree to which its occupants are subject to both the longitudinal and lateral forces to which the entire vehicle is subject.

This analysis also neglected effects on occupant comfort due to the presence or absence of passenger restraints, which automobiles have but trains typically do not. Bucket seats may further affect the passenger's ride experience as their raised front, side and rear 'lips' would tend to counteract the acceleration the vehicle is undergoing. Conversely, more restrictive seating configuration and passenger restraints in an automated car than are present on rail services may be associated with a further tension beyond that analyzed in this study: they may adversely affect the vehicle occupant's ability to perform certain types of leisurely and/or productive activities in-vehicle, and therefore may provide a further constraint that dampens the anticipated reduction in values-of-time. Research is required to quantify such effects.

Further research is needed to understand whether changes to road-use regulations would be required to prevent autonomous-car occupants from programming their cars to operate relatively smooth acceleration/deceleration profiles. At present, many jurisdictions restrict speed through maximum speed limits (and sometimes through minimum legal operating speeds), though research is required to better understand whether (and if so where and how) other operational characteristics that affect network capacity (such as rate-of-acceleration and length-of-inter-vehicle-headway) are regulated. Policy guidance may be desirable to more-narrowly bound the envelope of acceptable vehicle dynamics for autonomous road vehicles. A related policy issue is that the roll-out of autonomous cars might plausibly lead their users to demand higher standards of road maintenance (e.g. avoidance and filling of potholes) or design (e.g. wider turning-path radii) than at present, in order to ensure a high degree of leisure or productivity during the time that they are traveling in a car but not actively driving.

Another important line of inquiry for the upcoming research agenda is to establish how connected-vehicle concepts (e.g. automated platooning and cooperative behavior among conflicting traffic streams) – which aim in part to increase road network capacity – would interact with autonomous car occupants seeking a higher standard of ride comfort than car drivers currently experience. Research is also needed to establish human drivers' comfort when in a mixed-traffic context (some vehicles human-driven and some autonomously-operating) with the autonomous cars operating in platoons with small inter-vehicle headways (possibly following, i.e. 'tailgating', a leading human-driven vehicle.

Further research is needed to extend the current capabilities of traffic microsimulation software. For instance, rigorous, theoretically-grounded and user-customizable treatments of drivers' reaction time (cf. Basak et al., 2013) as well as the nature of their reactions are needed for researchers to robustly analyze the impacts of autonomously-operating cars' reduced reaction time and their unique signatures of reaction-to-stimuli.

This study was limited to car traffic only on a single type of road network (a signalized intersection) with one set of geometric characteristics. Further research is needed to understand the [non-] robustness of the findings we present here when more-diverse traffic streams (including non-motorized road users, commercial vehicles, etc.) and a wider range of geometric conditions are studied. It would be of substantial interest to policy-makers, for instance, to extend analysis of the sort presented here from a single, isolated signalized intersection to larger, real-world networks with real-world traffic demands. Such a model could be used to identify, on the basis of real-world journey patterns, the distribution of ride-quality experienced by each of the road network's autonomous car users. It would also be possible to analyze the implications of autonomous cars' occupants using novel criteria to navigate themselves through road networks (e.g. the consequences of routing strategies that aim to reduce the frequency and/or severity of high-acceleration/deceleration episodes).

Finally, further research is also needed to establish the impacts of other dimensions of ride quality beyond those explicitly modeled, notably vibration/oscillation (Wong, 2008).

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