Multiagent Spatial Simulation of Autonomous Taxis for Urban Commute: Travel Economics and Environmental Impacts

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Abstract: With the likelihood of autonomous vehicle technologies in public transport and taxi systems increasing, their impact on commuting in real-world road networks is insufficiently studied. In this study, an agent-based model is developed to simulate how commuters travel by autonomous taxis (aTaxis) in real-world road networks. The model evaluates the travel costs and environmental implications of substituting conventional personal vehicle travel with aTaxi travel. The proposed model is applied to the city of Ann Arbor, Michigan, to demonstrate the effectiveness of aTaxis. The results indicate that to meet daily commute demand with wait times less than 3 min, the optimized autonomous taxi fleet size is only 20% of the conventional solo-commuting personal car fleet. Commuting cost decreases by 38%, and daily vehicle utilization increases from 14 to 92 min When using internal combustion engine aTaxis, energy consumption, greenhouse gas (GHG) emissions, and SO_2 emissions are respectively 16, 25, and 10% higher than conventional solo commuting, mainly because of unoccupied repositioning between trips. Given the emission intensity of the local electricity grid, the environmental impacts of electric aTaxis do not show significant improvement over conventional vehicles. **DOI: 10.1061/(ASCE)UP.1943-5444.0000469.** *© 2018 American Society of Civil Engineers.*

Author keywords: Autonomous vehicle; Commute travel; Multiagent simulation; Environmental impact.

Introduction

Since 1969, commuters in the US have primarily traveled to work in personally owned vehicles; this has been the case for 90% of all commuters during the past two decades (Santos et al. 2011). Consequently, heavy traffic congestion easily occurs during peak commute hours, which generates hefty travel costs and considerable environmental impacts. For example, Los Angeles currently experiences the most severe traffic congestion in the US, with a typical half-hour commute taking 60% longer during the morning and 81% longer during the evening (Chew 2016). Light-duty vehicles, including passenger cars and light-duty trucks, are responsible for 61% of transportation greenhouse gas (GHG) emissions in the US (EPA 2016). Every year, over 2,200 premature deaths and at least $18 billion in health care costs in 83 of the largest urban areas in the US can be partly attributed to air pollution from traffic (Copeland 2011). Meanwhile, personal cars are unused for approximately 95% of the day (OECD 2015). The 2009 National Household Travel Survey (NHTS) data show that the average vehicle ownership per licensed driver is 0.99 (Santos et al. 2011). There are far more cars in the US than Americans need to reach their desired destinations according to current travel patterns in most locations (Fagnant and Kockelman 2014b).

Fully autonomous vehicles are expected to become a commercial reality in the next decade. Given the higher capital cost of early adoption, they are likely to be introduced first in public fleets and by Transportation Network Compnies (TNCs), such as Lyft, Uber, and Car2Go (Heard et al. 2018). Ridesharing and car-sharing companies are teaming up with automakers to introduce fleets of driverless taxis, which they envision becoming ubiquitous in urban areas. Autonomous taxis (aTaxis) may provide a solution to the problems presented above. The trajectory of technological progress suggests that aTaxis will eventually be able to travel anywhere a conventional vehicle can go. The use of aTaxis in car-sharing services may compete with conventional taxis or even shared taxi services because this new mode can bypass the costs associated with drivers (Liang et al. 2016; Zachariah et al. 2014). Specifically, aTaxi systems have the potential to reduce the average wait time and enhance ridematching experiences for passengers compared with conventional car-sharing programs (such as Zipcar and Car2go) with fixed rental and return stations; aTaxis may also reduce operating costs and provide more affordable service for low-income populations in comparison with app-based car-sharing programs (such as Uber) (Shen and Lopes 2015; Zhang et al. 2015a). Compared with personal vehicles, aTaxis may transform transportation from an owned asset into a subscription or pay-on-demand service, reducing vehicle ownership needs accordingly (Fagnant and Kockelman 2014b). Used in this way, aTaxis may enable consumers to make more spontaneous trips, be more productive, and/or have more time to relax during travel, in addition to providing more predictable and shorter travel times and improving rider safety (Burns et al. 2013).

This study analyzes the potential of using aTaxis as a transport mode for commuting travel rather than as a full replacement of

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existing transportation networks. The objective of this study is to optimize aTaxi fleet size to meet commuting demand, keeping wait times below an acceptable threshold and minimizing the system vehicle miles traveled (VMT). The corresponding environmental performance and total travel cost of this system are evaluated using an agent-based modeling (ABM) method. The commuting model simulates heterogeneous travel patterns to anticipate aTaxi system implications for various travelers who previously commuted in personal vehicles. This research contributes to the understanding of the impact of autonomous vehicles in three areas. First, the simulation is based on a real road network. Second, the hidden travel costs related to the value of commuters' time are considered. Third, the environmental impacts of internal combustion engine (ICE) aTaxis and electric aTaxis are both evaluated.

The paper is organized as follows. First, the ABM literature on autonomous vehicles is reviewed to inform the development of our method for modeling the commute with aTaxis in an urban road network. The method is shown and explained in detail in subsequent sections. Next, the application of the model to Ann Arbor, Michigan, in the US is presented, followed by the main results of several scenarios. Conclusions are drawn from the simulation results and potential directions for future research are offered.

Literature Review

Several modeling efforts have addressed the potential impacts of autonomous vehicles on traffic networks. Fagnant and Kockelman (2014b) designed an agent-based model for autonomous vehicle-sharing throughout a *grid-based* urban area and concluded that one shared autonomous vehicle (SAV) could replace approximately 11 privately owned vehicles, traveling 10% more distance than comparable nonshared trips but also resulting in improved environmental impact. Boesch and Ciari (2015) suggested that agent-based transport models are suitable for modeling future transport scenarios that incorporate autonomous vehicles. They discussed some possible research questions related to autonomous vehicles, such as potential future car fleet size, prospective demand patterns, and possible interactions between public transport and autonomous vehicles. Burns et al. (2013) applied a relatively simple analytical model to the case of Ann Arbor, Michigan, and concluded that autonomous vehicle-sharing could enhance mobility at considerably lower cost than privately owned vehicles. Zellner et al. (2016) used an agent-based approach to examine how interventions such as using autonomous shuttles and making streetscape enhancements for pedestrians and cyclists may mitigate the first/last mile problem of public transit; they also considered other factors such as parking fees and fuel costs. They simulated four Chicago neighborhoods with different densities and income levels; automated shuttle buses were assumed to have no capacity constraints. They concluded that a dedicated automated shuttle service could support significant mode shifts by increasing the utilization of public transit. Liang et al. (2016) simulated the use of electric automated taxis for the first/last mile of train trips with the objective of maximizing daily profits by optimizing service zone locations and which reservations were accepted. However, the model only considered trips occurring in the service zone, thus ignoring interzonal trips. Additionally, the model assumed that all the origins and destinations of passengers' requests were coming from or going to the center of the service zone. The automated taxis were treated as "flows" rather than as independent vehicles, which means that the model did not represent the battery recharging needs of specific vehicles.

Zhang et al. (2015a) used agent-based modeling to study the effect of shared autonomous vehicles on urban parking demand by varying fleet size and passenger wait time in a hypothetical city laid out in a *grid network*. Their simulation results indicated that with a low market penetration rate of 2%, SAV users reduced their parking demand by 90%. Fagnant and Kockelman (2015a) used an agent- and network-based simulation to deliver a benefit-cost analysis for fleet size optimization with dynamic ridesharing based on a system of SAVs in Austin, Texas. The authors concluded that dynamic ridesharing could reduce overall vehicle miles traveled, thus avoiding new congestion problems. Chen et al. (2016) simulated the operation of shared autonomous electric vehicles (SAEVs) under various vehicle range and charging infrastructure scenarios in a *gridded city* modeled roughly on Austin, Texas and predicted that with each SAEV replacing 5–9 privately owned vehicles, the unoccupied VMT could be reduced by 3–4%, with average wait times between 2 and 4 min. Martínez et al. (2016) developed an agent-based model to simulate a station-based one-way car-sharing system by dividing the city of Lisbon into a homogeneous grid of 200 m by 200 m cells in which trips were generated between two grid cells at each hour. Martínez et al. (2014) proposed an agent-based simulation model to assess the market performance of newly shared taxi service in Lisbon. They identified set of rules for space and time matching between the shared taxis and passengers, but ignored the interactions between passengers and vehicles (such as the waiting time limit of passengers). Levin et al. (2017) used realistic flow models to make predictions about the benefits of replacing personal cars with SAVs and found that, without dynamic ridesharing, the additional unoccupied repositioning trips made by SAVs increased congestion and travel times. However, this model was based on a downtown grid network, and intrazonal trips were not considered. Zhang and Guhathakurta (2017) examined the influence of SAVs on urban parking demand based on a real transportation network with calibrated link level travel speeds; however, in this research the trips always started and ended at the traffic analysis zone (TAZ) centroid and intrazonal travel time was ignored.

Table 1 summarizes previous studies related to shared autonomous vehicle modeling. Most of the research done so far on this topic has been simulated on a highly developed grid or hypothetical city and is constrained by several assumptions, such as a grid-based transportation network, constant travel speeds across the network, and passengers with uniform travel behavior. Furthermore, the planning and operation of autonomous taxis on commuting travel has received less attention. The present work seeks to fill these knowledge gaps.

Proposed Multiagent Model

This study utilizes agent-based modeling to simulate the anticipated autonomous vehicles' effect on commute travel. Agent-based models (ABMs) are well suited for modeling and studying the impacts of traffic behavior (Lu and Hsu 2017). Du and Wang (2012) suggested that an ABM approach can explore explanations, testify regarding assumptions, and predict changes in or the emergence of individual behaviors resulting from urban change. ABMs enable the representation of highly heterogenous and behaviorally complex populations of agents, and enable the modeling, both spatially and temporally, of large-scale interactions between agents for the study of dynamic but coherent system behaviors (Eppstein et al. 2011). One of the benefits of the agent-based computational process approach is that no complicated mathematical algorithms are

Table 1. Previous studies related to shared autonomous vehicle modeling

Reference	Objects	Method	Transportation network	Findings
Fagnant and Kockelman (2014b)	SAV	ABM	Grid city	One SAV could replace eleven private cars with 10% more VMT and improve environmental impacts
Burns et al. (2013)	SAV	Analytical model	None	SAVs have lower costs than private cars
Zellner et al. (2016)	Autonomous shuttles	ABM	None	Autonomous shuttles could enhance the use of public transit
Liang et al. (2016)	Electric automated taxis	Mathematical models	Nodelink network	Electric automated taxis used for first/last mile of train trips
Zhang et al. (2015a)	SAV	ABM	Grid city	SAV users reduced their parking demand by 90% with a low market penetration rate of 2%
Fagnant and Kockelman (2015a)	SAV	ABM	Nodelink network	Dynamic ride sharing could reduce overall vehicle miles traveled, thus avoiding new congestion problems
Chen et al. (2016)	Shared autonomous electric vehicles	ABM	Grid city	Each SEAV could replace five to nine privately owned vehicles
Martínez et al. (2016)	Car sharing	ABM	Grid city	Car sharing performed worse than private cars both in terms of time and cost
Martínez et al. (2014)	Shared taxi	ABM	Nodelink network	Shared taxis could lead to reductions in average waiting time and average taxi system fares
Levin et al. (2017)	SAV	Realistic flow models	Nodelink network	SAVs could increase congestion and travel times without dynamic ride sharing
Zhang and Guhathakurta (2017)	SAV	Discrete event simulation	Nodelink network with calibrated speed	Parking land use could be reduced by 5% once SAVs serve 5% of the trips within the city of Atlanta

required. The agents are driven by rational behaviors, and irrelevant aspects are ignored. These features of ABMs may explain their increasing popularity in studies of transportation logistics and traffic flow. Miller and Heard (2016) suggested that agent-based models can help define reasonable scenarios of technology deployment and evaluate designs that can lower transportation-related emissions.

The model is implemented with GAMA 1.7.0, a software platform for constructing spatially explicit agent-based simulations. Integrating a geographic information system (GIS) and traffic simulation leads to a more realistic representation of real-world transportation activities (Cai et al. 2012). Fig. 1 shows how our research was conducted according to the following steps:

1. Collect commute and spatial data of the study city, including the road network, the geographic distribution of office, commercial, and residential buildings, commuting speed, and a number of commuting trips by trip start time.
2. Use agent-based modeling to understand how a system of aTaxis will perform in meeting the daily commute demand.
3. Optimize fleet size to (1) ensure that wait times are below an acceptable threshold during peak hours and (2) minimize total VMT.
4. Once the fleet size is known, evaluate the available travel cost and environmental impacts of this commuting system.
5. Compare the travel cost and environmental performance of the aTaxi scenario with the personal car scenario.

Simulation Environment and Agents

Commuting demand is concentrated in two peak periods: 6:00–9:00 a.m. and 4:00–6:00 p.m. Given that for the first possible commute, the trip begins at 12:00 a.m., and for the last return commute, the trip begins at 11:59 p.m. (Santos et al. 2011), 0:00:00–23:59:59 was chosen as the service period of the aTaxi. Twenty four hours of commute behaviors were simulated in 5 min time steps, resulting in 288-time steps in the 24-h service period. In the model, office and residential buildings are represented as the origin and destination of trips, and real road networks are followed during the commutes.

There are two types of agents in the model—commuter agents and aTaxi agents. Commuters, who place a request to an aTaxi, and individual aTaxis, which set their shortest route paths for transporting commuters to their destinations, behave according to the well-known Floyd–Warshall algorithm (Aini and Salehipour 2012), one of the most efficient algorithms for finding the shortest

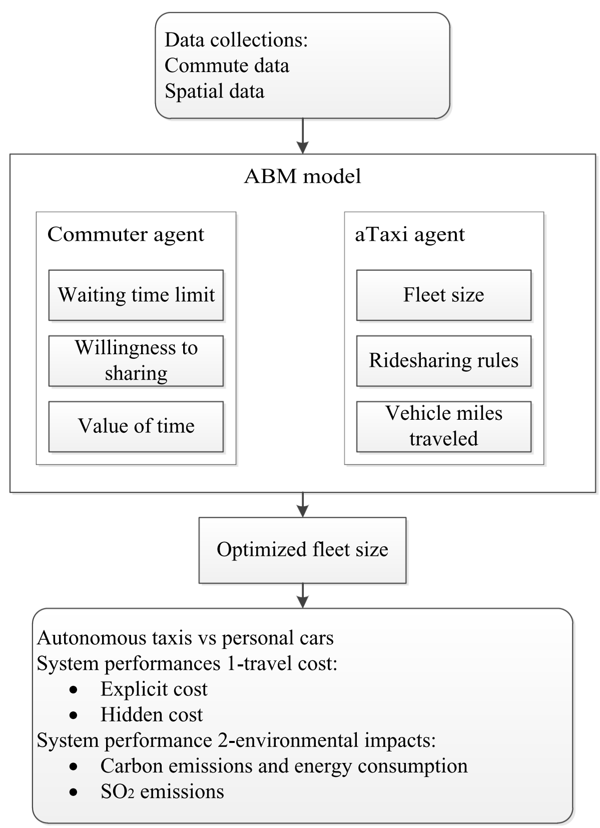

Fig. 1. Research workflow.

path between any two nodes in a given network (Floyd 1962; Warshall 1962).

Commuters

Every commuter has two spatial parameters: home (a residential building) and workplace (an office building). Population density is based on the spatial distribution of commuters' home locations at the beginning of the simulation. People commute between home and workplace every weekday, with most starting their commute between 6:00 and 9:00 a.m. and beginning their journeys home around 4:00–6:00 p.m. Commuters' departure times from home and workplace obey the normal distribution. The 20,000 commuters have their choice of transportation, personal car or aTaxi. Krueger et al. (2016) showed that travel cost, travel time, and waiting time might be decisive factors influencing the adoption of SAVs and the acceptance of dynamic ridesharing. In our model, commuters have different hourly incomes that obey a lognormal distribution. Commuters' waiting time limits are uniformly distributed and vary from 1 to 5 min. Commuters can decide whether or not to share vehicles with others. Commuters that choose not to share bear a higher travel cost. Zhang et al. (2015b) showed that the average hourly income for ridesharing commuters is 13% lower than the national average. Hence, commuters' willingness to share is negatively correlated to their hourly income in the model.

Autonomous Taxis

Based on commuters' willingness to share, there are two types of aTaxis, one that can be shared by multiple passengers, and one that can pick up and drop off a single passenger. The second condition occurs when (1) a passenger is not willing to share an aTaxi with others or (2) an aTaxi does not show up before reaching the waiting time limit of the potential second passenger. Idle aTaxis are randomly distributed in the city at the beginning of the simulation. During the simulation, aTaxis park directly at the last passenger's destination if not assigned to the next trip. They picks commuters up from their homes and bring them to their workplaces or pick them up from their workplaces and bring them home. The maximum capacity of an aTaxis is set as four. Only passengers that have the same trip starting hour have the potential to share a vehicle. The vehicles used in the model operate at different travel speeds based on the time of day. To realistically simulate traffic congestion during peak hours, vehicle travel speed depends on the number of vehicles on the road and the road capacity [Eqs. (1) and (2)]. In Eq. (2), the free-flow speed is a theoretical distance per time unit that a vehicle can travel without the presence of other vehicles (Jeerangsuwan and Kandil 2014); this value is set at 53.1 km/h (33.0 mi/h) (Zhang et al. 2015a). The aTaxi optimizes its route to deliver all onboard commuters to their respective destinations. An optimized route is the shortest distance between the highest α_v (speed coefficient) to deliver all the commuters to their destinations. The aTaxis' scheduled routes are first-come, first-served for commuters willing to share rides, as will be explained in detail in the next section

$$\alpha_v = e^{\frac{-N_{\mathrm{road}}}{RC}}$$

$$\alpha_v \in [0.10, 1.00] \tag{1}$$

$$v = \alpha_v \times v_{ff} \tag{2}$$

where N_{road} = number of vehicles on the road; RC = road capacity; v = vehicle speed; and v_{ff} = vehicle's free flow speed.

Interactions among Agents

Ride Sharing

Ride sharing appears to be essential for sustainable adoption of autonomous vehicle use to mitigate congestion and environmental consequences (Taiebat et al. forthcoming). Fagnant and Kockelman (2015a) showed that VMT may rise by over 8% if no ride sharing is allowed in satisfying travel demand with autonomous taxis. Zhang et al. (2015b) found that autonomous vehicle ride sharing offers superior service to a non-ride-sharing autonomous vehicle system, through shorter trips, lower trip costs, lower VMT, and, in the long run, better environmental outcomes. In this study, commuters can choose to participate in ridesharing if they are willing.

There are four operational parameters in the model: *waiting time limit, occupancy, added distance*, and *in-vehicle time. Waiting time limit* is the maximum time a passenger will wait between when the passenger requests a vehicle and when the vehicle arrives for pickup. If passengers cannot get an aTaxi within the waiting time limit, they use their personal car as usual. *Occupancy* is the number of passengers in the aTaxi, which varies from 0 to 4. Ride sharing occurs when occupancy is greater than 1. According to Zachariah et al. (2014), to share a ride, an additional occupant cannot increase the distance of any direct trip by more than 20%. Thus, *added distance* should be 20% less than the random original distances between passengers' homes and workplaces. For example, consider two potential passengers who want to travel from their workplaces to home, Passenger A and Passenger B. Passenger A's home location and workplace location are A_h and A_w, respectively, and Passenger B's home location and workplace location are B_h and B_w, respectively. The following equations need to be satisfied for ridesharing to occur. The aTaxi location when Passenger B asks to share a ride is denoted by B_{request}. The added distance algorithm is defined in Eqs. (3)–(5) as

$$d_{B_{\mathrm{request}}-Bw} \leq t_B \times v \tag{3}$$

$$d_{A_w-B_w-A_h-B_h} \leq 1.2 \times d_{A_w-A_h} \tag{4}$$

$$d_{A_w-B_w-A_h-B_h} \leq 1.2 \times d_{B_w-B_h} \tag{5}$$

where d = distance; and t = waiting time limit.

The aTaxi first takes Passenger A home because of the first-come, first-served rule. The aTaxi then stops to board additional passengers if the maximum capacity has not been reached. This study only considers ridesharing in SAV scenarios and assumes all commuters drive individually with their personal vehicles in the business as usual (BAU) scenario. In the SAV scenario, there are two mode choices, aTaxi and personal car (PC). Passengers choose different transport modes based on their waiting time limit and the waiting time for the closest aTaxi. In the BAU scenario, *occupancy* and *added distance* are set to 1 and 0, respectively, and passengers' wait time is 0. *In-vehicle time* represents the time spent in the traveling vehicle, which is converted into cost in economic evaluations.

Travel Costs

Travel cost is the primary concern for people choosing among different transport modes. One of the objectives of this study is to minimize the total travel cost in the commuting system, based on the passenger perspective. Some studies have used detailed cost categories to estimate the total cost for the operation of an SAV system, including vehicle costs (capital, running, and maintenance costs), infrastructure costs, and fleet management service costs based on various operational scenarios (Bösch et al. 2017; Chen and Kockelman 2016). This research only considers service cost for commuters. Operational costs undoubtedly account for a large proportion of a system's costs for transportation network companies, but from a consumer point of view, economics is the primary influence on the decision to adopt and utilize the system. In this study, the explicit financial costs of the service for commuters are considered, as well as the hidden costs associated with the time invested in various mobility-related activities. This analysis has received less attention in the literature compared to the operational cost of systems.

Explicit Costs

The regular fare for UberX (nonsurge periods) consists of a base fare of $1 and a $1.65 booking fee, plus $1.30 per mile plus $0.26 per minute. As aTaxis do not need drivers, their operating costs are lower (Liang et al. 2016). In consideration of these cost reductions and other factors, Fagnant and Kockelman (2015a) set their simulated nonshared trip price to $1.00 per mile (less than a third of the average taxi cab rates in Austin, Texas). Simulation results from Burns et al. (2013) showed that the costs per trip-mile of personal cars and SAVs were $0.75 and $0.41, respectively, without considering decreased parking costs and the value of time. Bauer et al. (2018) estimated that the lowest cost of service provided by shared automated electric vehicles fleet could be $0.29–$0.61 per revenue mile. Spieser et al. (2014) concluded that a mobility system featuring autonomous vehicles could be almost half as expensive as a system based on conventional human-driven cars. An average $1 per trip-mile fare for nonshared aTaxis was assumed, and personal car costs were assumed to be $1.4 per trip-mile based on the aforementioned price ratio of aTaxis and personal cars. In ride sharing situations, the *explicit cost* after picking up the next passenger is shared by all the passengers based on their trip distances.

Hidden Costs

Value of time (VOT) here is defined as "the monetary valuation of the total time invested in mobility-related activities" (Ellram 2002; Spieser et al. 2014). The time spent requesting, waiting, entering, and traveling is monetized with passengers' VOT based on level of comfort. Less comfortable trips incur a higher cost (Spieser et al. 2014). For example, personal trips on local roads during free-flowing traffic are priced at 50% of the median wage (Manpower-Research 2015) but the cost of traveling during heavy traffic is represented at 150% of the median wage (Victoria Transport Policy Institute 2013). Commuters experience a higher level of comfort in aTaxis, because they can use their travel time to perform other activities (reading, eating, talking, texting, sending email, or watching a movie). Zhang et al. (2015a) and Wadud (2017) contended that the personal valuation of travel time may decline as passengers reap productivity gains due to time free from driving. In contrast, Yap et al. (2016) showed that in-vehicle time in autonomous vehicles is experienced more negatively than in-vehicle time in manually driven cars because of the influence of travelers' negative attitudes regarding the trustworthiness and sustainability of autonomous vehicles. After considering these research results, the personal trip time in aTaxis and personal cars was priced at 20 and 67% of personal wages, respectively (Spieser et al. 2014). For example, when the wage is $28.40/h (the median wage in Ann Arbor), the corresponding VOT in aTaxis is approximately $5.68/h, one-third of the VOT in personal cars, which is $19.03/h. Table 2 summarizes the parameters for the total travel cost evaluation.

Table 2. Components of total travel cost

Travel cost	Personal car	aTaxi
Explicit cost	$1.40 per trip-mile for nonshared trip	$1.00 per trip-mile for nonshared trip
Hidden cost	$19.03/h with median wage level	$5.68/h with median wage level

Environmental Impacts

According to Fagnant and Kockelman (2014a), even gasoline-powered SAVs could substantially reduce negative environmental impacts by consuming approximately 16% less energy and generating 48% less volatile organic compound emissions per person-trip compared to conventional vehicles. However, Miller and Heard (2016) argued that the GHG emissions of autonomous vehicles could decrease on a functional unit basis (i.e., per-passenger-mile); overall transport-related GHG emissions increase as VMT increases (Brown et al. 2014; Morrow et al. 2014). Added VMT may also amplify drawbacks associated with high automobile use, such as increased gasoline consumption and oil dependence and higher obesity rates (Fagnant and Kockelman 2015b). Zhang et al. (2015b) indicated that although SAV systems tend to generate more VMT, the vehicle life cycle GHG and air pollutant emissions and energy consumption could still be reduced due to fewer cold starts and reductions in parking infrastructure requirements. Fagnant and Kockelman (2014b) acknowledged that relative to personal cars, the reduced parking needs of aTaxis could reduce emissions as well as traffic congestion.

GHG and pollutant emissions from conventional vehicles could be further ameliorated through the use of low-emission and energy-efficient drivetrain technologies (Taiebat et al. forthcoming). Fully electrically-powered fleets could eliminate all tank-to-wheel emissions from car travel (OECD 2015). Chen et al. (2016) showed that SAVs and electric vehicle technology have natural synergies. Thus, electric aTaxis have been integrated into this commuting system. Hawkins et al. (2013) found that electric vehicles (EVs) powered by the present European electricity mix could decrease global warming potential (GWP) 10–24% compared to conventional diesel or gasoline vehicles, assuming lifetimes of 150,000 km. The specific energy requirements for operating light-duty vehicles are approximately $0.30–0.46\ \mathrm{kW \cdot h/mi}$ (Kintner-Meyer et al. 2007), and the average emission rates of the DTE energy system serving Michigan electric customers are about $1.4\ \mathrm{kg/MW \cdot h}$ ($3.1\ \mathrm{lbs/MW \cdot h}$) for SO_2 and $884.5\ \mathrm{kg/MW \cdot h}$ ($1{,}950\ \mathrm{lbs/MW \cdot h}$) for CO_2 (Parks et al. 2007), making the SO_2 and GHG emissions of electric aTaxis straightforward to estimate.

The vehicle life cycle inventories from Chester and Horvath (2008, 2009) are used, which include parking infrastructure. In our model, it is assumed that personal cars and aTaxis are all conventional gasoline sedans. Following Fagnant and Kockelman (2015a), aTaxis are assumed to have a 250,000-mi service life; this aligns with the expected 7-year service life of Canadian taxis, which typically log more than 248,000 mi over their lifetimes (Stevens and Marans 2009), although SAVs may actually offer longer service due to their smoother automated driving profile. Life-cycle environmental impacts of autonomous vehicles and light-duty vehicles (Fagnant and Kockelman 2014b; Zhang et al. 2015b) were the basis for the environmental impacts of aTaxis and personal cars shown in Table 3. Only *energy consumption*, *GHG emissions*, and SO_2 *emissions* are considered.

Case Study of the City of Ann Arbor

Model Experiment Settings and Initialization

In this section, a detailed view of a city's existing commuting patterns, topology, and other characteristics used to build a

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Table 3. Potential environmental impacts of aTaxis and personal cars per vehicle-mile traveled

Environmental impact	Personal cars	aTaxis	Electric aTaxis
Energy consumption (MJ/VMT)	4.96	4.35	3.48
GHG emissions (kg CO2eq/VMT)	0.36	0.34	0.27
SO_2 emissions (g/VMT)	0.12	0.10	0.60

transportation model are presented. Recently passed legislation in Michigan allows self-driving vehicles to operate on any Michigan roadway, which widens opportunities for autonomous vehicle development (Burden 2016). Ann Arbor is representative of small- to medium-sized cities in the United States, based on the data from the 2009 NHTS. The city covers an area of 44 mi^2 and has a population of 117,770 (City-Data 2013). Among the 39,095 people who live and work in Ann Arbor, 50% (around 20,000) drive single-passenger vehicles to work, 20% walk to work, 11% take the bus, and 5% bike to work, according to the Washtenaw Area Transportation Study's most recent transit profile, conducted in 2009 (Biolchini 2013). Our analyses focus on the 20,000 people that drive alone in their commuter travels (the BAU scenario in this study).

The model is based on an area of 6.97 × 6.29 mi that contains the city of Ann Arbor. Taking advantage of Ann Arbor Open Data, the spatial information for buildings, roads, and city boundaries are incorporated into the model (City-Services 2017). In Fig. 2, the residential and office buildings are represented by different colors (grey for residential and purple for office/commercial), which serve as the origins and destinations of commuter travels within Ann Arbor. The population density in the model is based on the spatial distribution of residential buildings. The vehicles are shown as red squares. For people shown as circles, different colors depict the different objectives, with blue denoting "working" people traveling from home to work, and yellow depicting "resting" people traveling from work to home. The median income of Ann Arbor residents is \$56,835 per year, which translates into \$28.4/h (40 h/week, 50 weeks/year). Table 4 shows the basic parameters used in the Ann Arbor case study.

Table 4. Basic modeling parameters

Parameter	Value
Service area	6.97 × 6.29 mi
Average speed	44.4 km/h (27.60 mi/h)
a.m. peak	6:00–9:00
p.m. peak	16:00–18:00
Free-flow speed	53.1 km/h (33.0 mi/h)
Commute period	0:00:00–23:59:59
Commuters' average hourly income	\$28.4/h
Maximum aTaxi occupancy	4

Model Validation

Using real-world data to calibrate and validate the behavior model increases the credibility of and trust in this agent-based model and its results. Three components were used to validate the commuting

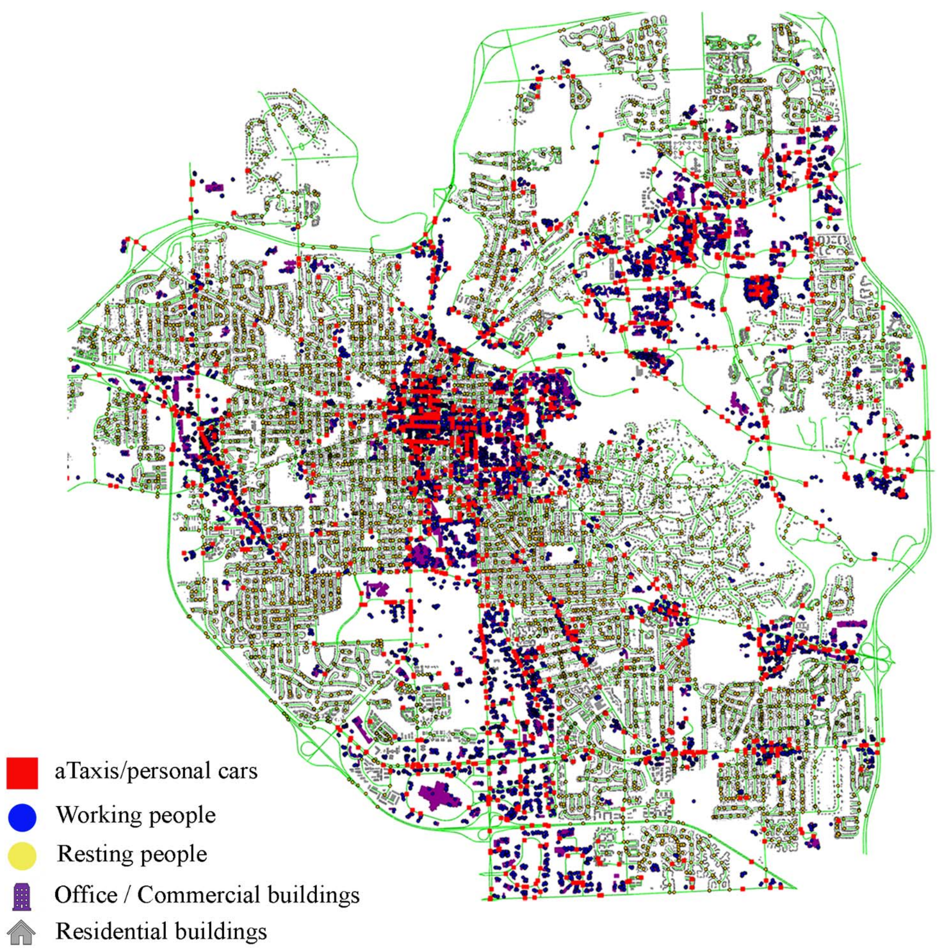

Fig. 2. Ann Arbor commute model.

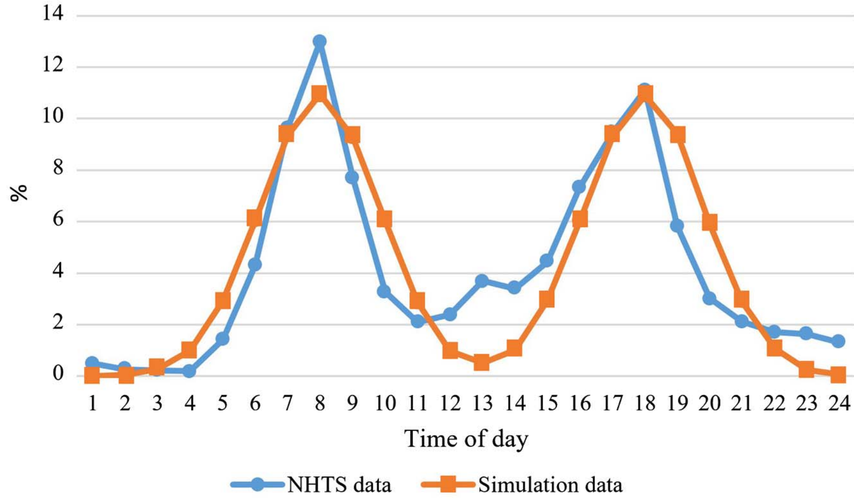

Fig. 3. Commute trips within Ann Arbor by start time of trip on weekdays.

model based on the BAU scenario: commute speed, commute time, and commute trips by time of day. The commute speed and commute time were collected from an Ann Arbor commuting survey (City-Data 2013). The survey data indicated an average commute speed of 44.4 km/h (27.60 mi/h); the corresponding simulation result was 44.3 km/h (27.52 mi/h). The average surveyed commute time within Ann Arbor was 10 min, and the commute time from the simulation results was 7.44 min. This difference can be explained by the inclusion of boarding and alighting time in the survey data; commute time from the simulation results only considered driving time. Data from the 2009 National Household Travel Survey (NHTS) were used to validate the commute trips by time of day (Fig. 3). These data contain extensive information about each commuting trip made by individuals living and working in small- to medium-sized cities, including start times of daily trips to work and return trips home. In Fig. 3, the morning peak hours of commuting travel are from 6 to 9 a.m., and the evening peak hours are from 4 to 6 p.m. In the simulation, the start times of trips to work and trips home both follow a normal distribution. The simulation data in the figure have the best fit with the NHTS data.

Scenario Simulation

Several scenarios were used for the evaluation of autonomous taxi performance in commuting trips. The same random number was used in the simulation runs for different scenarios to ensure that any difference in outputs would not be caused by noise from the random number seed that starts the simulation. All simulation results were generated from 100-run Monte-Carlo simulations. These scenarios were generated by varying three principal parameters in the simulation: fleet size, vehicle types, and operation strategies.

- Fleet size: In the BAU scenario, the fleet size equaled the commuting population (commuters who drive alone to work). In the SAV scenarios, the aTaxi fleet size was also related to the commuting population, but was varied from 10 to 90% of the BAU commuting population in 10% steps.
- Vehicle types: The BAU scenario represented the current situation—20,000 people commuting alone in their cars. In the SAV scenarios, there were two kinds of scenarios simulated—an all aTaxi scenario and a mode choice scenario. In the all aTaxis scenario, all personal cars were replaced with aTaxis, and people could choose whether to share aTaxis with others or not. In the all aTaxi scenario, 50% of the people driving alone to work in the BAU scenario could only choose aTaxis as their commute mode, while the other 50% of the people kept their previous commute modes, such as walking or cycling, which were not covered in this study. In the mode choice scenario, the 50% of people driving alone to work could choose aTaxis or personal cars based on their waiting time limit and the waiting time for the closest aTaxi. The electric aTaxi system was also simulated, with the environmental impacts compared to the personal car system. Full battery-electric vehicles have a limited range compared to gasoline vehicles and thus need time for recharging (OECD 2015). Nonetheless, Taiebat et al. (forthcoming) indicated that it is easier to integrate electric propulsion vehicles into a dynamic ride-sharing system than into a non-ride-sharing system, as the former has longer and more frequent chargeable breaks during the daytime. Electric aTaxis were assumed to have a fast battery recharge time of 30 min (using Level III chargers) and a vehicle range of 110 mi (Chen et al. 2016).
- Operation strategies: In the optimized fleet size scenario, several vehicle operation strategies were tested for further performance optimization. At the beginning of the simulation, idle aTaxis were randomly distributed in the city (Zhang et al. 2015a), or the empty aTaxis were spatially clustered according to population or building density. During the simulation, the aTaxis either parked directly at the last passenger's destination if they were not assigned to their next trip (OECD 2015) or they gravitated toward high-demand areas based on population or building density after sending their last passengers to their destinations (Zhang and Guhathakurta 2017).

Fig. 4 shows travel times for the SAV and BAU scenarios (the average wait time for the BAU scenario was 0 min, because people can drive their own cars anytime they like). In the SAV scenarios, when all the commute modes are aTaxis (the all aTaxis scenario), waiting time was reduced from 2.88 to 0.70 min, because the fleet size was larger. In the SAV scenarios when passengers have mode choice, the waiting time for the aTaxi fleet was relatively short, between 0.61 and 0.13 min, because passengers could choose the most convenient mode.

Table 5 shows the VMT of the SAV and BAU scenarios. Compared with the BAU scenario, as fleet size increased in the SAV scenarios, total VMT and unoccupied VMT increased. This was

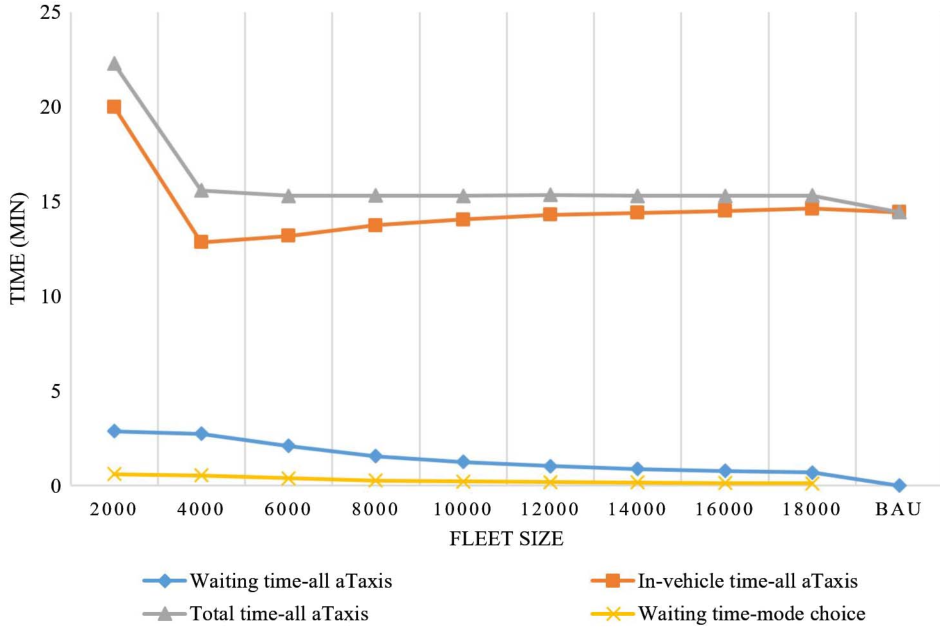

Fig. 4. Travel time for SAV and BAU scenarios.

Table 5. Vehicle miles traveled for SAV and BAU scenarios

SAV fleet size	VMT—aTaxi (miles)		VMT—PC (miles)		Unoccupied VMT (miles)		Total VMT (miles)	
	All aTaxis	Mode choice	All aTaxis	Mode choice	All aTaxis	Mode choice	All aTaxis	Mode choice
2,000	160,394	123,047	0	32,799	3,247	746	160,394	155,846
4,000	170,246	113,118	0	55,822	8,686	1,253	170,246	168,940
6,000	171,652	111,735	0	59,839	9,691	1,315	171,652	171,574
8,000	171,457	111,174	0	60,289	9,643	1,264	171,457	171,463
10,000	171,419	111,650	0	59,693	9,666	1,306	171,419	171,343
12,000	171,334	111,900	0	59,455	9,624	1,302	171,334	171,355
14,000	171,193	112,481	0	58,736	9,602	1,308	171,193	171,217
16,000	171,463	112,111	0	59,353	9,671	1,292	171,463	171,464
18,000	171,450	111,735	0	59,775	9,670	1,267	171,450	171,510
BAU	0		127,462		0		127,462	

Note: VMT—aTaxi is the VMT traveled by aTaxis; VMT—PC is the VMT traveled by personal cars (PC); and unoccupied VMT is the cruise distance, between car location at time of request and pickup location, that aTaxis accumulate when commuters request a ride.

a result of the cruise distances that aTaxis accumulated when commuters requested rides. The total cruise distances were be longer when there were more aTaxis. But total VMT did not increase drastically with larger fleet sizes, because the service aTaxis provide overlaps with commuting activities already performed without aTaxis.

In the SAV scenarios, the simulation results of the all aTaxis and mode choice scenarios were compared. In the mode choice scenario, unoccupied VMT were much smaller than in the all aTaxis scenarios. The total VMT in the all aTaxis and mode choice scenarios were very close. However, a significantly larger fleet size (more vehicles) was needed in the mode choice scenario. For example, only 4,000 aTaxis were needed to serve 20,000 passengers in the all aTaxis scenario, but in the mode choice scenario, 10,555 personal cars and 2,539 aTaxis were needed. This was because passengers with mode choices turn to personal cars as their commuting mode when aTaxis could not arrive within their waiting time limit. It can be concluded that the waiting time is still a big challenge for aTaxis compared with personal cars.

Results and Discussion

The final ideal fleet size was determined by passengers' wait time, in-vehicle time and total VMT. The optimized fleet size was determined when the average waiting time was less than 3 min, the average in-vehicle time was less than 15 min per trip, and the VMT was minimized throughout the simulation day (Zhang et al. 2015a, b). The optimized fleet size in this study was 4,000, 20% of the fleet size in the BAU scenario. The average wait time was 2.74 min, and the VMT increased by 33.6% because of the unoccupied vehicle travel of the aTaxis. Because there is little difference in total VMT for the all aTaxi and mode choice scenarios and many fewer vehicles are needed in the all aTaxis scenario, the optimized scenario uses 4,000 aTaxis in the all aTaxis scenario.

To further minimize the total VMT and average wait time, several operation strategies were tested. Fig. 5 shows the operation algorithm for aTaxis. Some of the operation strategies were mentioned previously— location of initial parking and behavior after serving the last passenger. High-demand areas refer to high population density areas or high building density areas. Ride sharing

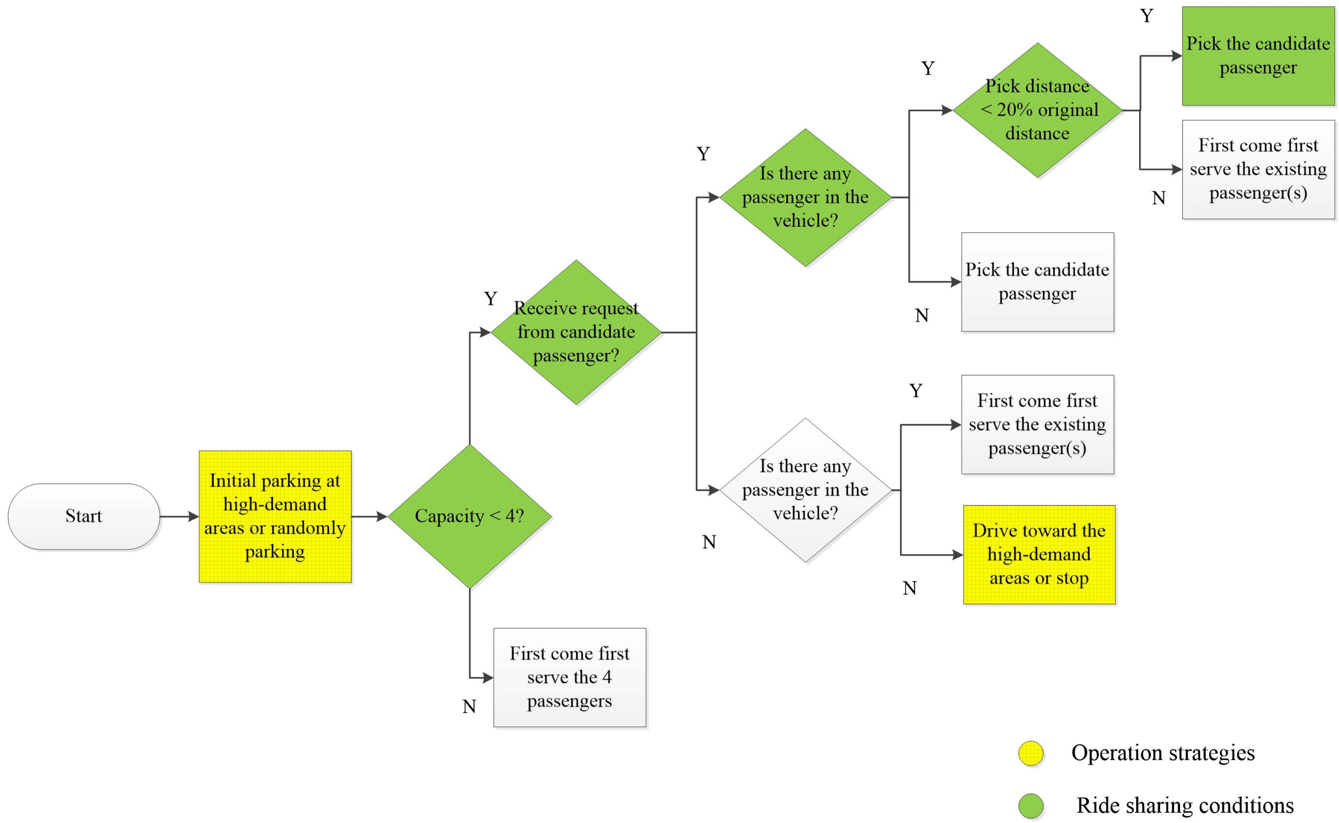

Fig. 5. Operation strategies of aTaxis.

only occurs when all the conditions for ride sharing are satisfied. The low rate of ridesharing can be explained. Table 6 shows some representative simulation results. The first column shows the origin condition—empty aTaxis are randomly distributed in the initial stage and park at the location of the last passenger's destination before receiving a new request. The second column shows the best simulation results, in which the total VMT are minimized and the average wait time is less than 3 min. Although the fourth and fifth columns show less wait time and higher ridesharing rates, the total VMT is significantly larger. Thus, the operation algorithm in the second column (in which empty vehicles park based on population density at the beginning of the simulation and wait at the location of the last passenger's destination until receiving a new request) was used for the following simulation.

In the optimized fleet size scenario, vehicle utilization for daily commuting improved to 92 min as opposed to the BAU scenario, in which privately owned vehicles were typically used for 14 min in daily commute travel. The average occupancy was 1.3 in the optimized fleet size scenario. This may reflect the low probability of matching trips that satisfy the ridesharing algorithm, a phenomenon in accord with the findings of Zhang et al. (2015a).

Total travel cost is composed of explicit costs and hidden costs, which are highly sensitive to the level of VMT and VOT. The more vehicle miles traveled, the greater the total travel cost. The VMT in

Table 6. Simulation results of respective operation strategies

Results	Number 1	2	3	4	5
Initial parking based on					
Population density	N	Y	N	Y	Y
Building density	N	N	Y	N	N
Drive toward areas with high					
Population density	N	N	N	Y	N
Building density	N	N	N	N	Y
Fleet size	4,000	4,000	4,000	4,000	4,000
Total VMT (miles)	170,246	168,233	168,293	290,331	290,680
Unoccupied VMT (miles)	8,686	8,635	8,681	8,246	8,389
In-vehicle time (min)	12.85	12.94	12.93	14.26	14.29
Wait time (min)	2.74	2.68	2.69	1.54	1.54
Total ridesharing	4,112	4,195	4,063	4,582	4,472

Note: Y = yes; and N = no.

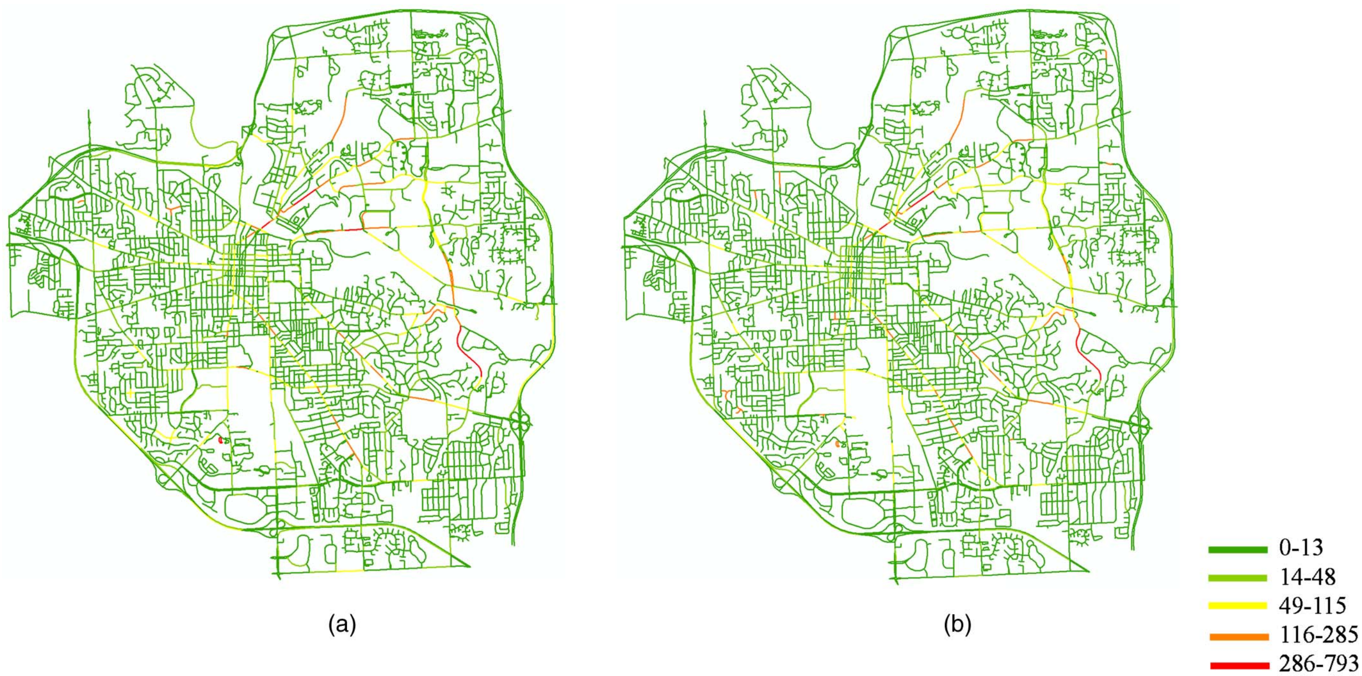

Fig. 6. Road occupancy of the optimized: (a) SAV scenario (fleet size = 4,000); and (b) BAU scenario (fleet size = 2,000).

aTaxis is higher because of the distance that vehicles travel while unoccupied as they drive to pick up passengers. The lower the value of time, the lower the total travel cost. In aTaxis, passengers are relieved from driving and can use their time as desired. Their productivity can be improved by working while riding in aTaxis. Therefore, the VOT for aTaxis is significantly lower. Overall, for ride-sharing trips in the optimized SAV scenario, the average total cost per mile was approximately \$1.29 (\$1.0 in explicit costs and \$0.29 in hidden costs), which was 38% lower than the non-ride-sharing trips in the BAU scenario.

In contrast, the environmental performance of the aTaxis system was not positive, because the environmental impact of the transportation system is highly related to VMT, and VMT was higher in the SAV scenarios because of unoccupied vehicle travel. In the optimized SAV scenario, system energy consumption, GHG emissions, and SO_2 emissions were 16, 25, and 10% higher, respectively, than in the BAU scenario. The environmental results were consistent with Miller and Heard (2016): autonomous vehicles may be more environmentally friendly on a functional unit basis (i.e., per passenger-mile), but overall transport-related GHG emissions increase as VMT increases. Environmental outcomes did not improve in the electric aTaxi scenario when the fleet size was set to 4,000. Although the corresponding system energy consumption and GHG emissions were 7 and 1% lower, respectively, than those in the BAU scenario, total SO_2 emissions increased by 560% compared to the BAU scenario. This was mainly due to the carbon emission intensity of Michigan's grid mix. Thus, environmental performance did not improve as expected with the introduction of autonomous vehicles for commuting in Michigan.

It is also found that, although aTaxis require far fewer vehicles than are currently on the road, the total distance traveled was greater because of unoccupied aTaxi travel as the vehicles accommodate the geographical distribution of demand. To explore road conditions with the introduction of aTaxis, road occupancy was studied (Fig. 6). Road occupancy represents the total number of vehicles using a specific road on one weekday. In the optimized SAV scenario, average road occupancy increased by 12% compared with the BAU scenario; however, as suggested by Zakharenko (2016), increased traffic does not necessarily cause an increase in congestion, because the SAVs are expected to run efficiently. Traffic congestion should be further investigated with more factors, such as direction of travel. This unexpected traffic problem was due to low rates of ride sharing and increased VMT in the SAV scenarios. The results indicate that policymakers and planners should not view vehicle automation through rose-colored glasses as a solution to traffic jams and environmental implications.

In the simulations for Ann Arbor, aTaxis were only used for end-to-end trips, because the city has no mass transit system. Using aTaxis to connect the first/last mile of trips on transit systems will be explored further in future work. Given the relatively small size of Ann Arbor, the results from this work are not representative for other cities, especially large metropolitan areas in which the average commute time is over 1 h per day. Future studies will develop similar agent-based models for large metropolitan areas with long, complex commute patterns. In addition, we only considered how the income of commuters affects their willingness to share rides. The role of social and racial factors, which are equally important to ride sharing, will be further examined in the future. Meanwhile, more realistic features can be added to this modeling framework, such as the consideration of traffic signals and further validation of the model through vehicle trips that cross main intersections.

Conclusions and Policy Recommendations

This study developed a simulation model to evaluate the travel costs and environmental impacts of aTaxis for commuting. The major contribution of the model described in this paper is to simulate aTaxis traveling on a real road network in which all vehicles start and end their trips and travel on the road. Moreover, hidden travel costs related to commuters' value of time were considered, and the environmental impacts of aTaxis were estimated to compare electric aTaxis, gasoline aTaxis, and conventional gasoline cars.

J. Urban Plann. Dev., 2018, 144(4): 04018033

The optimized fleet size was obtained with minimized VMT and reasonable average wait times for passengers; this study determined the optimized fleet size to be 20% of the fleet size in the BAU scenario. The results of the optimized fleet size scenario show a 38% reduction in total commute costs and an increase in the daily vehicle utilization from 14 to 92 min; however, daily road occupancy increased by 12%. The system's energy consumption, GHG emissions, and SO_2 emissions were 16, 25, and 10% higher, respectively, compared to the BAU scenario. This was mainly due to increased unoccupied VMT and less ride sharing. The unsatisfactory environmental performance of aTaxis was not improved when gasoline aTaxis were converted to electric aTaxis; the corresponding energy consumption and GHG emissions were 7 and 1% lower, respectively, than those in the BAU scenario, but SO_2 emissions increased to 560% compared to the BAU scenario.

Our simulation results show that aTaxis do not exhibit significant improvements in environmental performance compared to personal car use until more people are willing to share aTaxis rides. A clear policy implication of this study is that aTaxi fleets do not naturally lead to the higher environmental performance of transportation systems. Thus, tailored regulations must be in place before deployment of this technology to ensure that the design and operation of aTaxi systems are environmentally compliant. Our model is not designed as an accurate forecasting tool but rather as an initial test of the potential application of aTaxis to commuting travel. The model can be used to evaluate other prototypes in order to inform policy discussions among planners and decision makers, as well as to highlight gaps in existing methods that other model developers can consider in order to improve future simulations.

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Supplemental Data

The aTaxi simulation video is available online in the ASCE Library (www.ascelibrary.org).

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