Research Article

Multi-Agent 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 prior to privately-owned vehicles increasing, their actual 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, MI to demonstrate the effectiveness of aTaxis. Our results indicate that to meet daily commute demand with wait times less than 3 minutes, the optimized autonomous taxi fleet size is only 20% of the conventional solo-commuting personal car fleet. The commuting cost decreases by 38%, and daily vehicle utilization increases from 14 minutes to 92 minutes. In case of utilizing internal combustion engine aTaxis, energy consumption, GHG emissions, and SO_2 emissions are respectively 16%, 25%, and 10% higher than conventional solo commuting, mainly due to 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.

Keywords: Autonomous vehicle, Commute travel, Multi-agent simulation, Environmental impact

Introduction

Since 1969, commuters in the U.S. have primarily traveled to work in personally-owned vehicles, representing 90% of all commuters during the past two decades (Santos et al., 2011). Consequently, heavy traffic congestion can easily occur during commute peak hours, which can generate hefty travel costs and considerable environmental impacts. For example, Los Angeles currently experiences the most severe traffic congestion in the U.S., with a typical half-hour commute taking 60% longer during the morning and 81% longer during the evening (Jonathan, 2016). Light-duty vehicles, including passenger cars and light-duty trucks, are responsible for 61% of transportation greenhouse gas (GHG) emissions in the U.S. (EPA, 2016). Every year over 2,200 premature deaths and at least $18 billion in health care costs in 83 of the U.S.'s largest urban areas can be partly attributed to air pollution from traffic (Larry, 2011). Meanwhile, personal cars remain 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 U.S. 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 corporations, such as Lyft, Uber, and Car2Go (Heard et al., 2018). Ride-sharing and car-sharing companies are teaming up with automakers to introduce fleets of driverless taxis, which they see as becoming ubiquitous in urban areas. Autonomous taxis (aTaxis) may provide a solution to the problems presented above. The trajectory of technological progress suggests 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 ride-matching experiences for passengers compared with a conventional car-sharing program (such as Zipcar and Car2go) with fixed rental and return stations, and aTaxi also can reduce the operating costs and provide more affordable service for low-income populations compared with app-based car-sharing programs (such as Uber) (Shen and Lopes, 2015, Zhang, et al., 2015a). Compared with personal vehicles, aTaxis can transform transportation from an owned asset into a subscription or pay-on-demand service, with vehicle ownership needs to be reduced accordingly (Fagnant and Kockelman, 2014b). Used in this way, aTaxis can 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 while 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 substitution of existing transportation networks. The objective of this study is to optimize the aTaxi fleet size to meet the commuting demand, keeping the wait times below an acceptable threshold while minimizing the system vehicle miles traveled (VMT). Then 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. The 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; And third, the environmental impacts of the 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 the subsequent section. Then the application to Ann Arbor, MI in the U.S. is presented, followed by the main results of several scenarios. The conclusions drawn from the simulation results, and finally, 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 an autonomous vehicle (SAV) could replace approximately eleven privately-owned vehicles, traveling 10% more distance than used for comparable non-shared trips, but also resulting in an improved environmental impact. Boesch and Ciari (2015) suggested agent-based transport models are suitable for modeling future transport scenarios that incorporate autonomous vehicles. They discussed some possible research questions on 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, with consideration to other factors such as parking fees and fuel costs. Four Chicago neighborhoods with different densities and income levels were simulated, and the 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 through optimizing service zone locations and which reservations were accepted. However, the model only considered trips are occurring in the service zone, thus ignoring inter-zonal trips. Additionally, it assumed all the origins and destinations of passengers' requests are coming or going to the center of the service zone. And the automated taxis were also treated as "flows" rather than as independent vehicles, which means that the battery recharging needs of specific vehicles were not represented.

Zhang et al. (2015a) used agent-based modeling to study the effect of shared autonomous vehicles (SAV) on urban parking demand by varying the 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 ride-sharing based on a system of SAVs in Austin, Texas. The authors concluded that dynamic ride-sharing 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 SEAV replacing 5-9 privately-owned vehicles, the unoccupied VMT could be reduced by 3-4%, with average wait times between 2 and 4 minutes. 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 200m by 200m cells, where trips are 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. A set of rules for space- and time-matching between the shared taxis and passengers was identified, but the interactions between passengers and vehicles (such as the waiting time limit of passengers) were ignored. 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 ride-sharing, the additional unoccupied repositioning trips made by SAVs increased congestion and travel times. However, the model is based on a downtown grid network, and intra-zonal trips are not considered. Zhang et al. (2017) examined the influence of SAVs on urban parking demand based on a real transportation network with calibrated link level travel speeds, but the trips always start and end at the Traffic Analysis Zone (TAZ) centroid and the intra-zonal travel time is ignored.

Table 1 summarizes previous studies related to shared autonomous vehicle modeling. As it appears, 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 grid-based transportation network, constant travel speed across the network, and passengers with uniform travel behavior. Furthermore, planning and operation of autonomous taxis on commuting travel have received less attention. The present work seeks to fill these knowledge gaps.

Proposed multi-agent 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 an ABM approach can explore explanations, testify assumptions, and predict changes or emergence of individual behaviors upon urban change. ABMs enable representation of highly heterogenous and behaviorally complex populations of agents and modeling both spatially and temporally large-scale interactions between the 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 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) suggest 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, a software platform for constructing spatially explicit agent-based simulations (GAMA, 2016). Integrating a geographic information system (GIS) and traffic simulation leads to a more realistic representation of real-world transportation activities (Cai et al., 2012). **Figure 1** shows how the research is conducted according to the following steps:

Step 1: Collecting commute and spatial data of the study city, including road network, the geographic distribution of office, commercial, and residential buildings, commuting speed, and a number of commuting trips by trip start time.

Step 2: Using agent-based modeling to understand how a system of aTaxis will perform in meeting the daily commute demand.

Step 3: Optimizing the fleet size to ensure the wait times are below an acceptable threshold during peak hours while simultaneously minimizing total VMT.

Step 4: Once the fleet size is known, evaluating the available travel cost and environmental impacts of this commuting system.

Step 5: Finally, comparing 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 am and 4:00–6:00 pm. Given the first possible commuting, the trip begins at 12:00 am, and the last return commuting trip begins at 11:59 pm (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 using a time step of 5 minutes, resulting in 288-time steps in the 24-hour service period. In the model, office and residential buildings are represented as the origin and destination of those commuting trips, and the real road networks are followed during the commute trips.

There are two types of agents in this model, commuter agents, and aTaxi agents. Commuters who place a request to an aTaxi, and the individual aTaxis that set their shortest route paths serving the commuters to their destinations behave according to the well-known Floyd–Warshall algorithm (Aini and Salehipour, 2012), which is one of the most efficient algorithms for finding the shortest path between any two nodes in a given network (Floyd, 1962, Warshall, 1962).

(a) The 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 the home and workplace every weekday, with most starting their commute to work around 6:00–9:00 am and beginning their journeys home around 4:00–6:00 pm. Commuters' time leaving 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 that influence the adoption of SAVs and the acceptance of dynamic ride-sharing. In the model used here, commuters have different hourly incomes that obey a lognormal distribution. Commuters' waiting time limits are uniformly distributed and vary from 1 minute to 5 minutes. Commuters can decide whether or not to share vehicles with others. Commuters that choose not to share will bear a higher travel cost. Zhang et al. (2015b) showed that the average hourly income for ride-sharing commuters is 13% lower than the national average. Hence, commuters' willingness to share is negatively correlated to their hourly income in the model.

(b) The autonomous taxis (aTaxis)

Based on commuters' willingness to share, there are two types of aTaxis: one that can be simultaneously shared by multiple passengers; one that can pick up and drop off a single passenger. The second condition occurs when: 1) the 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. It picks commuters up from their homes then brings them to their workplace, or it picks them up from their workplaces then brings them home. The maximum capacity of aTaxis is set as four. Only passengers on the same trip starting hour have the potential to share a vehicle. The vehicles used in the model operate at different travel speeds by 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 (see **Eqs. (1)** and **(2)**). In **Eq. (2)**, the free-flow speed is a theoretical distance per time unit that a vehicle could travel without the presence of other vehicles (Jeerangsuwan and Kandil, 2014), which is set at 33 miles per hour (mph) (Zhang et al., 2015a). The aTaxi can optimize its route to deliver all on-board commuters to their respective destinations. An optimized route means the shortest distance between the highest α_v (speed coefficient) to deliver all the commuters to their destinations. The aTaxis' schedule routes are first-come, first-served for commuters willing to share rides, as explained in detail in the next section.

$$\alpha_v = e^{\frac{-N_{road}}{RC}} \tag{1}$$

$$\alpha_v \in [0.10, 1.00]$$

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

Where N_{road} is the number of vehicles on the road, RC is road capacity, v is vehicle speed, and v_{ff} is 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., 2018). Fagnant and Kockelman (2015a) showed that VMT might rise by over 8% if no ride-sharing is allowed in satisfying travel demand with autonomous taxis. Zhang et al. (2015b) also found that autonomous vehicle ride-sharing can offer superior service to a non-ridesharing autonomous vehicle system, through shorter trip delays, lower trip costs, less VMT generation, and, in the long run, better environmental outcomes. In this study, commuters can choose to participate in ride-sharing 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 passenger wait between when the passenger requests the vehicle and when the vehicle arrives for pick-up. If the passenger cannot get an aTaxi within the waiting time limit, he/she will use the personal car as usual. *Occupancy* is the number of passengers in the aTaxi, which varies from 0 to 4. Ride-sharing occurs when the occupancy is more 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, the *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 is the first passenger and passenger B is the potential second passenger. Passenger A's home location and workplace location are set as A_h and A_w and passenger B's home location and workplace location are set as B_h and B_w. The following equations need to be satisfied for the ride-sharing to occur. $B_{request}$ means the aTaxi location when passenger B asks to share a ride. The added distance algorithm is defined in **Eqs. (3), (4)** and **(5)** as:

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

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

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

Where d represents the distance, and t is 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 ride-sharing in the SAV scenarios and assumes all commuters drive individually with their vehicles in the business as usual (BAU) scenario. In the SAV scenarios, one scenario has two kinds of mode choices—aTaxi and personal car (PC). The passengers choose different transport modes based on their waiting time limit and the waiting time for the closest aTaxi. In the BAU scenario, the *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 cost

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 this commuting system based on the passengers' perspectives. Some studies used detailed cost categories to estimate the total cost for the operation of 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 the service cost for commuters. The operational costs undoubtedly account for a large proportion of system's costs for Transportation Network Companies, but travel economics for commuters largely influences the decision for adoption and utilization of system from a consumer point of view. 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 the system.

(a) Explicit cost

The regular fare for UberX (non-surge 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, operating costs are lower (Liang et al., 2016). With consideration of these costs reductions and other factors, Fagnant and Kockelman (2015a) set their simulated non-shared trip price to $1.00 per mile (less than a third of average taxi cab rates in Austin, Texas). The simulation results of 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 the 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 non-shared aTaxis was assumed here, and the personal car fee was assumed to be $1.4 per trip mile based on the price ratio of aTaxi and personal car mentioned above. In the case of sharing, the *explicit cost* after picking up the next passenger is shared by all the passengers, based on their trip distances.

(b) Hidden cost

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 for, entering, and traveling is monetized with passengers' VOT based on the 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), while the cost of traveling during heavy traffic is represented at 150% of the median wage (Institute, 2013). For aTaxis, commuters can experience a higher level of comfort, since they can use their travel time to perform other activities (reading, eating, talking, texting, sending an email or watching a movie). Zhang et al. (2015a) and Wadud (2017) also contend 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 an autonomous vehicle is experienced more negatively than in-vehicle time in manually driven cars, the travelers' negative attitudes regarding trust and sustainability of autonomous vehicles are major influences. After considering the above research results, the personal trip time in aTaxis and personal cars was priced at 20% and 67% of the personal wage, respectively (Spieser, et al., 2014). For example, when the wage is $28.40 per hour (the median Ann Arbor wage), the corresponding *VOT* in aTaxis is approximately $5.68/hour, which is one-third of that in personal cars, at $19.03/hour. **Table 2** summarizes the parameters for total travel cost evaluation.

Environmental impacts

According to Fagnant and Kockelman (2014a), even gasoline-powered SAVs could substantially reduce negative environmental impacts, 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) argue that the GHG emissions of autonomous vehicles could decrease on a functional unit basis (i.e., per-passenger-mile), while overall transport-related GHG emissions increase as VMT increases (Brown et al., 2014, Morrow III, 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) indicate that although SAV systems tend to generate more VMT, the vehicle life cycle GHG and air pollutant emissions and energy consumption can still be reduced due to fewer cold starts and reductions in parking infrastructure requirements.

Fagnant and Kockelman (2014b) also acknowledge that compared 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., 2018). 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 the global warming potential (GWP) 10% to 24% compared to conventional diesel or gasoline vehicles, assuming lifetimes of 150,000 km. The specific energy requirements to operate light-duty vehicles is around 0.30 - 0.46 kWh/mile (Kintner-Meyer et al., 2007), and the average emission rates of DTE Energy system serving Michigan electric customers are about 3.1 lbs/MWh for SO_2 and 1,950 lbs/MWh for CO_2 (Parks, et al., 2007), so the SO_2 emissions and GHG emissions of electric aTaxis are straightforward to estimate.

The vehicle life cycle inventories from Chester and Horvath (2008), Chester and Horvath (2009) are used, which include parking infrastructure. In our model, it is assumed that personal cars and aTaxis are all conventional gasoline sedans. Following the assumption of Fagnant and Kockelman (2015a), aTaxis are assumed to have a 250,000-mile service life, aligning with the expected 7-year service life of Canadian taxis, which typically log more than 248,000 miles over their lifetimes (Stevens and Marans, 2009), though 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.

A 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 transportation model are presented to. 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 square miles with 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). The analyses focus on the 20,000 people that drive alone in their commute travels, which is the BAU scenario in this study.

The model is based on an area of 6.97 miles × 6.29 miles containing Ann Arbor. Taking advantage of Ann Arbor Open Data, the spatial information for buildings, roads, and the city boundary are incorporated into the model (City-Services, 2017). In **Figure 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/hour (40 hours/week, 50 weeks/year). **Table 4** shows the basic parameters used in the Ann Arbor case study.

Model validation

Using real-world data to calibrate and validate the behavior model increases credibility and trust in this agent-based model and its results. Three components are used to validate the commuting model based on the BAU scenario: commute speed, commute time, and commute trips by time of day. The commute speed and commute time are collected from an Ann Arbor commuting survey (City-data, 2013). From the survey data, the average commute speed is 27.60 mph, and the corresponding simulation result is 27.52 mph. The average surveyed commute time within Ann Arbor is 10 minutes, and the commute time from the simulation results is 7.44 minutes, a difference that can be explained by the inclusion of boarding and alighting time in the survey data while the commute time from the simulation results only considers the driving time. Data from the 2009 National Household Travel Survey (NHTS) is used to validate the commute trips by time of day (**Figure 3**). These data contain extensive information about each commuting trip made by an individual living and working in small-medium cities, including the start times of daily trips to work and return trips home. In **Figure 3**, the morning peak hours of commuting travel are from 6 am to 9 am, and the evening peak hours are from 4 pm to 6 pm. In the simulation, the start time of trips to work and 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 is used in the simulation runs for different scenarios to ensure that any difference in outputs is not caused by noise from the random number seed that starts the simulation. All simulation results are generated from 100-run Monte-Carlo simulations. These scenarios are generated by varying three principle parameters in the simulation: fleet size, vehicle types, and operation strategies.

Fleet size: In the BAU scenario, the fleet size equals the commuting population (commuters who drive alone to work). In the SAV scenarios, the aTaxi fleet size is also related to the commuting population, which is varied from 10% to 90% of the BAU commuting population in 10% steps.

Vehicle types: The BAU scenario represents the current situation—20,000 people commuting alone by their cars. In the SAV scenarios, there are two kinds of scenarios simulated—an all aTaxi scenario and a mode choice scenario. In the all aTaxis scenario, all personal cars are replaced with aTaxis, and people can choose to share aTaxis with others or not. It means 50% of people driving alone to work only can choose aTaxis as their commute mode in all aTaxi scenarios, while the other 50% of people will still keep their previous commute modes, such as walking or cycling, which are not covered in this study. In the mode choice scenario, the 50% of people driving alone to work can choose aTaxis or personal cars based on their waiting time limit and waiting time for the closest aTaxi. The electric aTaxi system is also simulated, with the environmental impacts compared to the personal car system. Full battery-electric vehicles today still have limited range compared to gasoline vehicles and thus need time for recharging (OECD, 2015). Nonetheless, Taiebat et al. (2018) indicate that it is easier to integrate electric propulsion vehicle into a dynamic ride-sharing system than into a non-ridesharing system, as the former has longer and more frequent chargeable breaks during the daytime. Electric aTaxis are assumed to have a fast battery recharge time of 30 minutes (using Level III chargers) and a vehicle range of 110 miles (Chen, et al., 2016).

Operation strategies: In the optimized fleet size scenario, several vehicle operation strategies are tested for further performance optimization. At the beginning of the simulation, idle aTaxis are randomly distributed in the city (Zhang et al., 2015a), or the empty aTaxis are spatially clustered according to the population density or building density. During the simulation, the aTaxis park directly at the last passenger's destination if not assigned to the next trip (OECD, 2015), or the aTaxis gravitate toward high-demand areas based on population density or building density after sending the last passenger to its destination (Zhang et al., 2017).

Figure 4 shows the travel time of the SAV and BAU scenarios (the average wait time of the BAU scenario is 0 minutes as people can drive their car anytime they like). In the SAV scenarios when all the commute modes are aTaxis (all aTaxis scenario), the waiting time is reduced from 2.88 minutes to 0.70 minutes since the fleet size is larger. In the SAV scenarios when passengers have mode choice, the waiting time of the aTaxi fleet size is relatively short, between 0.61 minutes and 0.13 minutes, as the passengers can choose the convenient mode.

Table 5 shows the VMT of the SAV and BAU scenarios. Compared with the BAU scenario, as fleet size is increased in the SAV scenarios, the total VMT is increasing, and the unoccupied VMT is also increasing. This is a result of the cruise distances that aTaxis accumulate when commuters request a ride. The total cruise distance will be longer when there are more aTaxis. But the total VMT is not increased drastically with the larger fleet size, as the service aTaxis provide overlaps with the commuting activity already performed without aTaxis.

In the SAV scenarios, the simulation results of all aTaxis and mode choice scenarios are compared. In the mode choice scenario, the unoccupied VMT is much smaller than in all aTaxis scenarios. The total VMT in all aTaxis and mode choice scenarios are very close. However, significantly larger fleet size (more vehicles) is needed in the mode choice scenario. For example, only 4,000 aTaxis are needed to serve 20,000 passengers in the all aTaxis scenario, while in the mode choice scenario, 10,555 personal cars and 2539 aTaxis are needed. This is because passengers with mode choices turn to personal cars as the commuting mode when aTaxis cannot arrive within their waiting time limit. It can be concluded that the waiting time is still a big challenge for aTaxis compared with the personal cars.

Results and discussion

The final ideal fleet size is determined by passengers' *wait time*, *in-vehicle time* and total *VMT*. The optimized fleet size is determined when the average waiting time is less than 3 minutes, the average in-vehicle time is less than 15 minutes per trip, and the VMT is minimized throughout the simulation day (Zhang et al., 2015a, Zhang, et al., 2015b).The optimized fleet size here is 4,000, 20% of that in the BAU scenario. The average *wait time* is 2.74 minutes, and the *VMT* is increased by 33.6% because of the unoccupied vehicle travel of the aTaxis. As 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 are tested. **Figure 5** shows the operation algorithm of aTaxis. The blocks highlighted by yellow represent the operation strategies mentioned before: the location of initial parking and the behavior after serving the last passenger. High-demand areas refer to the high population density areas or high building density areas. The green blocks show the ride-sharing conditions. It can be found the ride-sharing only occurs when all the conditions are satisfied. The low rate of ride-sharing can be explained. Some representative simulation results are shown in **Table 6**. The first column shows the origin condition: the empty aTaxis are randomly distributed in the initial stage and park at the location of the last passenger's destination before receiving the new request. The second column shows the best simulation results, the total *VMT* is minimized, and the average *wait time* is less than 3 minutes. Although the fourth and fifth columns show less *wait time* and higher ride-sharing rate, the total *VMT* is significantly large. Thus, the operation algorithm in the second column (the empty vehicles park based population density at the beginning of the simulation, and wait at the location of the last passenger's destination until receiving the new request) are used for the following simulation.

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

The 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 aTaxis is increased due to 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. For aTaxis, passengers are relieved from driving, and they can use their time as desired. Their productivity can be improved through working in the aTaxis. Therefore, the *VOT* of the aTaxi is greatly reduced. Overall, for the ride-sharing trips in the optimized SAV scenario, the average total cost per mile is approximately \$1.29 (\$1.0 for explicit cost and \$0.29 for hidden cost), which is 38% lower than the non-sharing trips in the BAU scenario.

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

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

In the case of Ann Arbor, aTaxis are only used for end-to-end trips as there is no transit. Using aTaxis to connect the first/last mile trips of transit will be explored further in ongoing work. Given the relatively small size of Ann Arbor, the results from this work are not representative for other cities, especially large metropolitan areas where average commute time is over one hour per day. Future study will develop similar agent-based models for large metropolitan areas with long, complex commute patterns. In addition, we consider only the income of commuters affects their willingness to share. Social and racial factors, in fact, play equally important roles in ride sharing, which 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 crossing the main intersection.

Conclusion and policy recommendation

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, where all vehicles start and end their trips and travel on the road. Moreover, hidden travel costs related to commuters' value of time are considered, and the environmental impacts of aTaxis are estimated to compare electric aTaxis, gasoline aTaxis, and conventional gasoline cars.

The optimized fleet size is obtained with minimized VMT and reasonable average wait times for passengers—which this study determined to be 20% of the fleet size of the BAU scenario. The results of the optimized fleet size scenario show that total commute costs are reduced by 38% and the daily vehicle utilization is increased from 14 minutes to 92 minutes, but the daily road occupancy is increased by 12%. This system's energy consumption, GHG emissions, and SO_2 emissions increase by 16%, 25%, and 10%, respectively compared to the BAU scenario. This is mainly due to increased unoccupied VMT and less ride-sharing. The unsatisfactory environmental performance of aTaxis is not improved when gasoline aTaxis are converted to electric aTaxis: the corresponding energy consumption and GHG emissions can be 7 % and1% lower than those in the BAU scenario, while SO_2 emissions increase to 560% compared to 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 system. Thus, tailored regulations must be in place before deployment of this technology to ensure that the design and operation of aTaxi system are environmental-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 to improve future simulations.

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List of Tables

Table 1. Previous studies related to shared autonomous vehicle modeling

Papers	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 improved environmental impacts
Burns et al. (2013)	SAV	Analytical model	None	SAV had lower cost than private cars
Zellner, Massey, Shiftan, Levine, and Arquero (2016)	Autonomous shuttles	ABM	None	Autonomous shuttles could enhance the use of public transit
Liang et al. (2016)	Electric automated taxis	Mathematical models	Node-link 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	Node-link network	Dynamic ride-sharing could reduce overall vehicle miles traveled, thus avoiding new congestion problems
Chen, Kockelman, and Hanna (2016)	Shared autonomous electric vehicles	ABM	Grid city	Each SEAV could replace 5-9 privately-owned vehicles
Martínez, Correia, Moura, and Mendes Lopes (2016)	Car sharing	ABM	Grid city	Carsharing performed worse than private cars both in terms of time and cost
Martínez, Correia, and Viegas (2014)	Shared taxi	ABM	Node-link network	Shared taxi could lead to reduction in the average waiting time and average taxi system fare
Levin, Kockelman, Boyles, and Li (2017)	SAV	Realistic flow models	Node-link network	SAV could increase congestion and travel times without dynamic ride sharing
Zhang, Guhathakurta, and Ross (2017)	SAV	Discrete event simulation	Node-link network with calibrated speed	Parking land use could be reduced by 5% once the SAVs serve 5% of the trips within the city of Atlanta

Table 2. The components of total travel cost

Travel cost	Personal car	aTaxi
Explicit cost	\$1.40 per trip-mile for non-shared trip	\$1.00 per trip-mile for non-shared trip
Hidden cost	\$19.03 per hour with median wage level	\$5.68 per hour with median wage level

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

Environmental impacts	Personal cars	aTaxis	Electric aTaxis
Energy consumption (MJ/VMT)	4.96	4.35	3.48
GHG emissions (kg CO_{2eq}/VMT)	0.36	0.34	0.27
SO_2 emissions (g/VMT)	0.12	0.10	0.60

Table 4. Basic modeling parameters

Parameter	**Value**
Service area	6.97 mi. × 6.29 mi.
Average speed	27.6 mph
AM peak	6:00-9:00
PM peak	16:00-18:00
Free-flow speed	33 mph
Commute Period	0:00:00-23:59:59
Commuters’ average hourly income	$28.4/hour
Maximum aTaxis occupancy	4

Table 5. Vehicle mile traveled (VMT) of SAV and BAU scenarios

SAV Fleet size	VMT-aTaxi (mile)		VMT-PC (mile)		Unoccupied VMT (mile)		Total VMT (mile)	
	All aTaxis	Mode choice	All aTaxis	Mode choice	All aTaxis	Mode choice	All aTaxis	Mode choice
2000	160394	123047	0	32799	3247	746	160394	155846
4000	170246	113118	0	55822	8686	1253	170246	168940
6000	171652	111735	0	59839	9691	1315	171652	171574
8000	171457	111174	0	60289	9643	1264	171457	171463
10000	171419	111650	0	59693	9666	1306	171419	171343
12000	171334	111900	0	59455	9624	1302	171334	171355
14000	171193	112481	0	58736	9602	1308	171193	171217
16000	171463	112111	0	59353	9671	1292	171463	171464
18000	171450	111735	0	59775	9670	1267	171450	171510
BAU	0		127462		0		127462	

Note: *VMT-aTaxi* is the VMT traveled by the aTaxis. VMT-PC is the VMT traveled by the personal cars (PC). *Unoccupied VMT* is the cruise distances between car location at time of request and pick-up location that aTaxis accumulate when commuters requesting for a ride.

Table 6. The simulation results of respective operation strategies

Item		1	2	3	4	5
Initial parking	Population density	N	Y	N	Y	Y
based on	Building density	N	N	Y	N	N
Drive toward	Population density	N	N	N	Y	N
areas with high	Building density	N	N	N	N	Y
Fleet size		4000	4000	4000	4000	4000
Total VMT (mile)		170246	168233	168293	290331	290680
Unoccupied VMT (mile)		8686	8635	8681	8246	8389
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 ride-sharing		4112	4195	4063	4582	4472

Note: Y refers to Yes, and N refers to No.