The Impact of Private Autonomous Vehicles on Vehicle Ownership and Unoccupied VMT Generation

Wenwen Zhang *(Corresponding Author)*
Assistant Professor
Virginia Tech, Department of Urban Affairs and Planning
Room 215, Architecture Annex
140 Otey Street NW, Blacksburg, VA, 24060
Tel: 540-232-8431; Email: wenwenz3@vt.edu

Subhrajit Guhathakurta
Professor, Director of Center for GIS
Georgia Institute of Technology, School of City and Regional Planning
760 Spring Street NW, Suite 217, Atlanta, GA, 30308
Tel: 404-385-1443; Email: subhro.guha@design.gatech.edu

Elias B. Khalil
Ph.D. Student
Georgia Institute of Technology, School of Computational Science & Engineering
Klaus Advanced Computing Building, 266 Ferst Drive, Atlanta, GA 30313
Tel: 404-429-3015; Email: elias.khalil@cc.gatech.edu

ABSTRACT

With 36 ventures testing autonomous vehicles (AVs) in the State of California, commercial deployment of this disruptive technology is almost around the corner (California, 2017). Different business models of AVs, including Shared AVs (SAVs) and Private AVs (PAVs), will lead to significantly different changes in regional vehicle inventory and Vehicle Miles Travelled (VMT). Most prior studies have already explored the impact of SAVs on vehicle ownership and VMT generation. Limited understanding has been gained regarding vehicle ownership reduction and unoccupied VMT generation potentials in the era of PAVs. Motivated by such research gap, this study develops models to examine how much vehicle ownership reduction can be achieved once private conventional vehicles are replaced by AVs and the spatial distribution of unoccupied VMT accompanied with the vehicle reduction. The models are implemented using travel survey and synthesized trip profile from Atlanta Metropolitan Area. The results show that more than 18% of the households can reduce vehicles, while maintaining the current travel patterns. This can be translated into a 9.5% reduction in private vehicles in the study region. Meanwhile, 29.8 unoccupied VMT will be induced per day per reduced vehicles. A majority of the unoccupied VMT will be loaded on interstate highways and expressways and the largest percentage inflation in VMT will occur on minor local roads. The results can provide implications for evolving trends in household vehicles uses and the location of dedicated AV lanes in the PAV dominated future.

Keywords: Autonomous Vehicles, Vehicle Ownership, Unoccupied VMT

INTRODUCTION

Many vehicle manufacturers and IT companies have announced plans for deployment of autonomous vehicles by the year 2020. As of June 27th, 2017, 36 ventures have received permits to test prototypes of self-driving vehicles on road in California (California, 2017). This revolutionary transportation technology will undoubtedly alter household vehicle ownership and VMT generation patterns in cities (Fagnant & Kockelman, 2015a; Litman, 2014). The impact of AV on vehicle ownership and VMT generation depends heavily on the business models of the technology, including Shared AVs (SAVs) and Private AVs (PAVs). SAV is an envisioned self-driving taxi system. The operation of the SAV system is centralized to optimize the performance of the system. In the SAV model, consumers pay for mobility service rather than the fleet. Alternatively, the PAV model echoes the current vehicle business model, but replacing conventional vehicles with AVs.

Most of the existing studies focused on the impacts of SAVs, which are considered as more environmentally sustainable compared with PAVs. For instance, agent-based simulation models are developed to demonstrate the affordability and feasibility of the SAV system (Burns, Jordan, & Scarborough, 2013; Spieser et al., 2014) and to explore the impacts of SAVs on vehicle ownership, Greenhouse Gas (GHG) emissions, traffic flow, charging stations, and parking demand (Chen, Kockelman, & Hanna, 2016; Fagnant & Kockelman, 2014; Greenblatt & Saxena, 2015; Zhang & Guhathakurta, 2017; Zhang, Guhathakurta, Fang, & Zhang, 2015a, 2015b). Based on author's best knowledge, to date, only one report has explored the impact of PAVs on household vehicle ownership reduction potentials, using the 2009 National Household Travel Survey (NHTS) data (Schoettle & Sivak, 2015). The study only considers time conflicts in the household AV scheduling model, while other components such as the origins and destinations of trips are not included. Additionally, the study does not provide implications for unoccupied VMT generation, as the origins and destinations of trips are not provided in NHTS data.

Despite SAVs being more heatedly discussed in the existing literature, the privately-owned AVs (PAVs) may turn out to be more preferable to consumers, based on several recent AV preference survey results. Bansal et al. (2016) conducted an opinion survey in Austin. Among the 347 respondents, only 13% indicate they may be willing to give up personal vehicles and rely exclusively on SAVs whose costs are $1/mile. Additionally, the most optimistic scenario indicates over 35% of the respondents are unlikely to participate into the SAV program, regardless the cost of the service. Another SAVs preference survey suggests that given various trip characteristics profiles, more than 70% respondents choose not to use the SAV system (Krueger, Rashidi, & Rose, 2016). Another stated preference survey reveals that only 5.4% of the 1920 observations in North America are willing to rely exclusively on SAVs for commuting purposes trips and only 40.63% are willing to participate into the SAV program (even at zero membership cost) (Haboucha, Ishaq, & Shiftan, 2017). In sum, the majority of consumers may still prefer to own a private AV in the near future. Therefore, it is critical to gain a more comprehensive understanding regarding the impact of PAV on vehicle ownership and VMT generation.

Motivated by the limited understanding of the impacts of PAV on household vehicle ownership and unoccupied VMT generation, this study designs and implements a vehicle scheduling algorithm to estimate the vehicle ownership reduction potentials and unoccupied VMT generation in the era of PAV, using the 2011 travel survey data from Atlanta Metropolitan Area. Statistical analyses are then conducted to identify critical factors (such as household travel pattern, socio-economic, demographic, and built environment characteristics) that are associated with the vehicle ownership reduction potentials. Additionally, the study also examines the temporal and spatial distributions of unoccupied VMT using the synthesized trip profiles generated by the Atlanta Activity Based Travel model.

The remainder of the article is organized as follows. The subsequent section provides a brief overview regarding the existing studies regarding the impact of AVs on vehicle ownership and VMT generation. Section Three describes the data sources and methodology used to examine vehicle ownership reduction and unoccupied VMT generation potentials under PAV business model. Section Four presents and analyzes the model results. Conclusions and future research directions are discussed in Section Five.

BACKGROUND

With autonomous vehicles technology almost around the corner, the literature regarding the impact of AVs is proliferating. Many studies show this disruptive technology will improve travel experience by reducing crashes (Harper, Hendrickson, & Samaras, 2016), improve fuel efficiency (Fagnant & Kockelman, 2015a; Mersky & Samaras, 2016), and provide more reliable travel time, at a cost that is significantly more affordable than current private sedans (Burns et al., 2013; Litman, 2014). However, AVs, if owned privately, instead of shared among consumers, are also expected to generate several negative externalities, such as excessive VMT generation (Zhang et al., 2015b), Greenhouse Gas (GHG) emissions, and more transportation energy consumptions (Greenblatt & Saxena, 2015), stemming primarily from changes in travel behavior. The following sections summarize the existing studies regarding how AVs (either SAV or PAV) may influence vehicle ownership and VMT generation.

Most literature has focused on how SAVs would reduce vehicle ownership, using agent-based simulation models. Results show that one SAV can replace approximately 11-14 private vehicles (i.e. approximately 90% of reduction rate), assuming consumers are willing to give up personal vehicles and rely exclusively on SAVs (Bischoff & Maciejewski, 2016; Boesch, Ciari, & Axhausen, 2016; Fagnant & Kockelman, 2014, 2015b; Martinez & Crist, 2015; Rigole, 2014; Zhang et al., 2015b). The replacement rates vary slightly based on the population and employment density in the studied region. To authors' best knowledge, only one study, to date, explored how PAVs will influence household vehicle ownership. Schoettle and Sivak (2015) found that average household vehicle ownership can be reduced by 43% from 2.1 to 1.2, once households replace conventional vehicles with AVs, using weighted National Household Travel Survey (NHTS) data. However, in this study, the minimum required vehicle is estimated based on the trip starting and ending time. The location of origin and destination is not accounted for in their analyses, as such information is not provided in the NHTS data. While, in some cases, one AV may not be sufficient to serve two non-overlapping trips if the relocation time is too long. Therefore, Schoettle and Sivak's pioneering work only provides an optimistic upper bound for potential vehicle ownership reduction rate. Almost no other study, to date, has developed a model to understand vehicle reduction potential while incorporating the spatial distributions of origins and locations into the model. Additionally, little understanding has been gained regarding what type of household (i.e. socio-demographic, economic, and travel behavior characteristics) are more likely to reduce household vehicle ownership in the era of AVs.

The vehicle automation technology will undoubtedly change Vehicle Miles Travelled (VMT) for various reasons. First, several studies suggest that VMT would increase by 10-14%, once the AVs start to serve underserved population, especially those driving capability are constrained for various reasons (Harper, Hendrickson, Mangones, & Samaras, 2016). Second, VMT may also change dramatically, given variations in travel behaviors due to reduced travel time costs and parking costs (Childress, Nichols, Charlton, & Coe, 2015; Levin & Boyles, 2015). The changes in VMT may vary significantly based on the assumptions made in the simulations, ranging from -35% to 20%. Childress et al., (2015) suggest that VMT increase the most the perceived travel time costs are reduced by over 50%. Alternatively, VMT may decrease if the per mile based travel cost of AVs surplus the existing sedans. Finally, AVs can also introduce a significant amount of unoccupied VMT, during the relocation process. In the SAV model, 11%-20% of unoccupied VMT are generated, when SAVs relocate to serve clients or balance the spatial distribution of vehicles in the system. The range varies significantly depending on the level of willingness to share rides among consumers and the trip density (Fagnant & Kockelman, 2014; Zhang et al., 2015b). However, it remains unclear how much unoccupied VMT will be induced after replacing conventional household vehicles with AVs under the PAV business model. Additionally, it is also critical to understand the spatial and temporal distribution of unoccupied VMT to provide implications for future travel demand and the allocation of infrastructure resources correspondingly. However, few research has contributed to these topics.

To fill up the existing gaps, this study aims to examine potentials of vehicle ownership reduction in the era of PAV by incorporating the spatial distribution of origins and destinations into the model using weighted Atlanta travel survey. Additionally, this study also determines the spatial and temporal distribution of unoccupied VMT as a result of reduced household vehicle ownership, using synthesized regional travel profile output from Atlanta activity based model. The results will provide implications for vehicle reduction potentials and spatial and temporal distribution of unoccupied VMT in the region. The model outputs will shine lights on future transportation facility demand in a PAV dominated future.

DATA AND METHODOLOGY

Data

Two data sets are used in this study, including (1) 2011 Atlanta Travel Survey and (2) synthesized Atlanta trip profile from the Atlanta activity based travel model (ABM). Both datasets are generously provided by Atlanta Regional Commission (ARC). The 2011 Atlanta Travel Survey contains 10,278 households, 9,901of which (96% of the weighted sample) have at least one privately owned vehicles (excluding three households living outside of the region and eleven households with partial members filled out the survey). According to the survey data, each household produces approximately 9.12 vehicle trips per day and owns 1.99 vehicles, on average (ARC, 2011). The origin and destination of the trips have already been geocoded with longitudes and latitudes by ARC.

The synthesized trip profile includes characteristics of simulated trips for each synthesized household in the 20-county Atlanta metropolitan area. There are 2,115,034 households and 19,235,738 vehicle trips in this dataset. The data contain several trip features, including origin, destination, departure time (in 30 minutes intervals), travel mode, etc. The attributes of trips are simulated using their marginal distributions collected in the 2011 travel survey. Therefore, the 2015 trip profile can be considered as an extrapolated version of 2011 Atlanta Travel Survey for the entire 20-county metro area. This dataset occupies 4.2 Gigabytes of space on the disk and, therefore, is computationally challenging to process.

We use two datasets to examine different research questions, considering the characteristics/strength of each dataset. The travel survey includes information, such as longitudes and latitudes of trip origins and destinations and a wide range of socio-economic and demographic characteristics at the household and individual level. In other words, the travel survey data are more refined than the synthetic trip profile from ABM. Therefore, we use Atlanta travel survey trip records to determine vehicle reduction potentials of households and identify household features that are correlated with the vehicle reduction potentials. Meanwhile, although ABM trip profile only contains TAZ level trip origin and destination information and a limited number of household characteristics, the data do provide all Origin-Destination (OD) pairs in the study area. Therefore, the synthetic trips from ABM are used to determine the spatial distribution of unoccupied/relocation VMT in the transportation network.

Methodology

The research methodology is three-fold. In step one, a greedy algorithm is designed to determine the minimum number of private AVs needed to fulfill a household's current travel demand. In step two, mixed-integer programming (MIP) problems are formulated for households that can reduce vehicle ownership. The problems are then solved using IBM CPLEX software to obtain optimized vehicle route (i.e. the route that can minimize daily VMT for each household) to determine the origins and destinations of unoccupied trips. The above described two model components are applied to 2011 Atlanta travel survey data to examine vehicle reduction and unoccupied VMT generation potentials. Last, in step three, the models from step one and two are applied to the synthesized 2015 trip profile for the entire region to generate new Origin-Destination (OD) matrices. A trip assignment model is then implemented in CUBE to allocate unoccupied AV trips to the transportation network. The details for each step are described in the following sections.

In Step one, a greedy scheduling algorithm is designed to determine the minimum number of autonomous vehicles needed to satisfy the travel demand of all household members in each household. Frist, the vehicle trips generated in each household are sorted based on the trip departure time and are analyzed sequentially. At the beginning of the day, the vehicle inventory for the household is set as zero. For each incoming household trip, the algorithm will find all the AVs that will be available by the departure time of the trip. An AV is considered as available when two criteria are met: 1) AV is not serving other household member when the current trip departs and 2) There is sufficient time for AV to relocate from its location to the origin of the upcoming trip. The potential relocation time is obtained using Google Maps Distance Matrix Application Programming Interface (API) service. The Distance Matrix API returns Google's estimate of travel time given the provided trip origin, destination, and departure time. Therefore, the congestion factor on relocation is considered in this process. If no AV is available to serve the incoming trip, a new AV will be added to the household vehicle inventory. The location of the AVs will always be updated to the destination of the last served trip. Additionally, the status of AVs will be marked as busy until the end of the last served trip. After scanning all trips made by the household, the number of AV saved in the household vehicle inventory will be the minimum required number of AV to serve the household. Vehicle reduction potential is calculated by subtracting the existing number of operation vehicles (not the total number of owned vehicles) by the number of required AVs. It is assumed that extra vehicles that are not identified as daily operational vehicle in the survey are kept for purposes other than travel and therefore will not be eliminated after the introduction of AVs.

The above described greedy algorithm, however, cannot determine the excessive VMT generation of the household, as the vehicle service route is not optimized. Therefore, in step two

Mixed-Integer Programming problems are formulated and solved to determine the minimum amount of unoccupied VMT generated during AV repositioning process for households that can reduce vehicle ownership. The notation of the problems are as follows:

$v \in V$: the set of $|V|$ AVs;
$t \in T$: the set of $|T|$ trips made by household members;
$e \in E$: the set of $|E|$ potential relocations between household trips with e_{t_i,t_j} indicating relocation miles generated after serving t_i first and then t_j;
$x_{v,t_i,t_j} \in \{0,1\}$: if AV v relocates to serve trip t_i and t_j

For each household, a weighted directed graph (or network), $G = (T, E)$, is generated. The nodes (T) in the graph represent vehicle trips generated by the household. The directed edges (E) indicate the amount of relocation miles incurred if an AV serves both starting and ending trips/nodes sequentially. If there is no enough relocation time between the trips, then no edge will be generated, i.e., the two trips cannot be served by one PAV. In other words, if there is no sufficient time for AVs to relocation from the destination of prior trip to the origin of current trip before the departure time of the current trip, then the two trip nodes will not be connected by an edge. Similar to Step One, the relocation time is obtained using Google Distance Matrix API. The direction of the edge indicates the time sequence of the service. The objective of this optimization problem is to find $|v|$ disjoint path(s) in this graph, such that the sum of edge costs (relocation distance) is minimized, see the objective function below:

$$min \sum_{v=1}^{V} \sum_{i=1}^{T} \sum_{j=1}^{T} x_{v,t_i,t_j} * e_{t_i,t_j} \tag{1}$$

Having defined the variables (x_{v,t_i,t_j}), the problem graph $G = (T, E)$, and the set of AVs V, we are now ready to describe the *constraints* of our MIP problem. First, each trip should be served by exactly one AV. This suggests that the sum of x variables related to the incoming edge(s), $deg^-(t_i)$ of node i should be equal to one. Additionally, the sum of x variables related to the outgoing edge(s), $deg^+(t_j)$ of node j should also be constrained to one.

$$\sum_{v=1}^{V} \sum_{i} x_{v,t_i,t_j} = 1, \forall\, t_i \in \, deg^-(t_j) \tag{2}$$

$$\sum_{v=1}^{V} \sum_{i} x_{v,t_i,t_j} = 1, \forall\, t_j \in \, deg^+(t_i) \tag{3}$$

Second, the route of each AV should be contiguous, i.e. AVs cannot teleport from one location to another to serve trips. In other words, the incoming and outgoing edges of one node/trip should be assigned to one AV.

$$\sum_{t_j \in deg^{-}(t_i)} x_{v,t_i,t_j} = \sum_{t_j \in deg^{+}(t_i)} x_{v,t_i,t_j}, \forall\, t_i \in T, v \in V \quad (4)$$

Third, the number of AV(s) should not be more than the minimum required number of AV(s). To implement these constraints, hypothetical starting and ending nodes, H_0 and H_1, are added into the graph to control the number of AVs assigned to put into the network. The starting node has outgoing edges to all the trip nodes and the weight are all assigned to be zero. Similarly, the ending node has zero cost weighted incoming edges from all the trip nodes.

$$\sum_{v=1}^{V} \sum_{t=1}^{T} x_{v,H_0,t_i} = |v| \quad (5)$$

$$\sum_{v=1}^{V} \sum_{t=1}^{T} x_{v,t_i,H_1} = |v| \quad (6)$$

This optimization algorithm is then applied to households that can potentially reduce vehicle ownership to determine their unoccupied VMT generation. The optimization is implemented in Python 2.7 using IBM CPLEX's Python Application Programming Interface (API) (IBM, 2017). Descriptive statistics of the model outputs are calculated using weighted 2011 Atlanta travel survey to examine the overall vehicle reduction and unoccupied VMT generation potentials.

Finally, in step three, models from previous steps are applied to the 2015 synthesized trip profile to obtain the origins and destinations of all AV relocation trips on a typical weekday. There are some minor changes in the methodology from Step One and Two, so that the model can be applied to ABM data. ABM only contains TAZ level trip origin and destination information. Therefore, instead of using Google Distance Matrix API, we obtained relocation time using the SKIM matrix from ABM. After applying the revised model to ABM data, we obtained New Origin-Destination (OD) matrix, containing empty relocation AV trips, by time of the day. The vehicle trips (original trip and empty relocation trips) are then assigned to road segments by applying the all or nothing trip assignment process in CUBE voyager. Potential changes in the spatial distribution of traffic volume are then identified through cross-comparing with the current ARC baseline network outputs.

Model Assumptions and Scenarios

The assumptions and simplifications of the developed models are summarized as follows:

1) No change in the travel behaviors, i.e., no induced travel demand and no variations in the travel patterns (origin, destination, departure time);
2) The estimated VMT changes stems exclusively from the re-routing of unoccupied AVs from prior trip destination generated by another household member to the existing trip origin;
3) Vehicles are only shared among household members not among households;
4) It assumes a 100% market penetration rate and heterogeneity in the preferences for AVs is not considered

We also examined some other scenarios in the scenario development section. We specifically explored the impact of schedule flexibility, i.e., the tolerance on trip departure and arrival time. We discuss the results of the scenarios analysis in the schedule flexibility scenarios development section.

RESULTS

Vehicle Reduction Potentials

The results show that approximately 18.3% of the households in the weighted survey have the potential to reduce vehicle ownership even if they maintain the current travel schedule. Compared with the weighted vehicle inventory in the region, approximately 9.5% vehicle ownership reduction can be achieved overall. For households that can reduce vehicle ownership, on average, 1.1 vehicles can be eliminated. The majority of the households cannot achieve vehicle reduction given their overlapping trip schedules, especially during peak hours. More vehicle can be reduced if household members start to re-schedule daily trips to accommodate AVs.

We developed a logistic regression model to understand the correlations between socioeconomic and demographic characteristics of households (i.e., explanatory variables) and vehicle ownership reduction potentials (i.e., the dependent variable). The results, as displayed in Table 1, indicate that current vehicle dependency plays an important role in vehicle ownership reduction potential. Households with more operating vehicles are more likely to benefit from the vehicle automation technology. Additionally, the reduction potential is also correlated with the trip generation pattern of the household. The vehicle ownership reduction potential is larger for households with higher trip generation rates and shorter trips. This type of travel pattern leaves more room for PAV relocation in the future. The results also suggest households with different socioeconomic features are more likely to benefit from PAVs. Families with higher income and home owners (rather than renters) have more potential to reduce vehicle ownership. Additionally, households with more workers are also more likely downsize their existing vehicle ownership, once vehicles can relocate from work locations to serve family members in other places in the region. Finally, the results also indicate that built environment features are also correlated with vehicle ownership reduction potentials. The vehicle reduction potential for suburban households is larger, as the estimated coefficients for variables such as log transformed housing unit density and four-way intersection density are negative and significant at 95% level, while the coefficient for log transformed distance to the Central Business District (CBD) is positive and significant. Atlanta is a monocentric city, the model results suggest that households in suburban areas, which are further away from downtown and are less intensively developed, are more likely to be able to reduce vehicle ownership in the future.

TABLE 1 Logistic Regression Results Summary

Variables	Coefficients	Std. Err.	Z	P > |z|
Operating Vehicle Count	2.213	0.069	31.960	0.000
Trip Generation Rate	0.099	0.016	6.242	0.000
Average Trip Distance (Mile)	-0.042	0.007	-6.286	0.000
Low Income Household (annual income < 30,000)	-0.466	0.130	-3.587	0.000
Number of Workers	0.383	0.043	8.952	0.000
Home Renter Dummy	-0.612	0.133	-4.605	0.000
Single Adult Household	-2.154	0.162	-13.333	0.000

Log (distance to CBD)	0.102	0.018	5.776	0.000
Log (Housing Units Density)	-0.124	0.031	-3.997	0.000
Four-way Intersection Density (per Mile^2)	-0.010	0.003	-2.939	0.003
Sample Size (N)	9007			
Pseudo R-square	0.45			
Log-likelihood	3070.0			

Excessive VMT generation

In return for vehicle ownership reduction, the households will generate more unoccupied VMT during the vehicle relocation process. Households, on average, will produce 29.8 more VMT per day per reduced vehicle. The distribution of excessive VMT generation per household suggest that most households increase VMT by around 10-20 miles per day, see Figure 1. The median increase in VMT is 26.5 mile per household. Less than 10% of the households will generate 67 more miles per day.

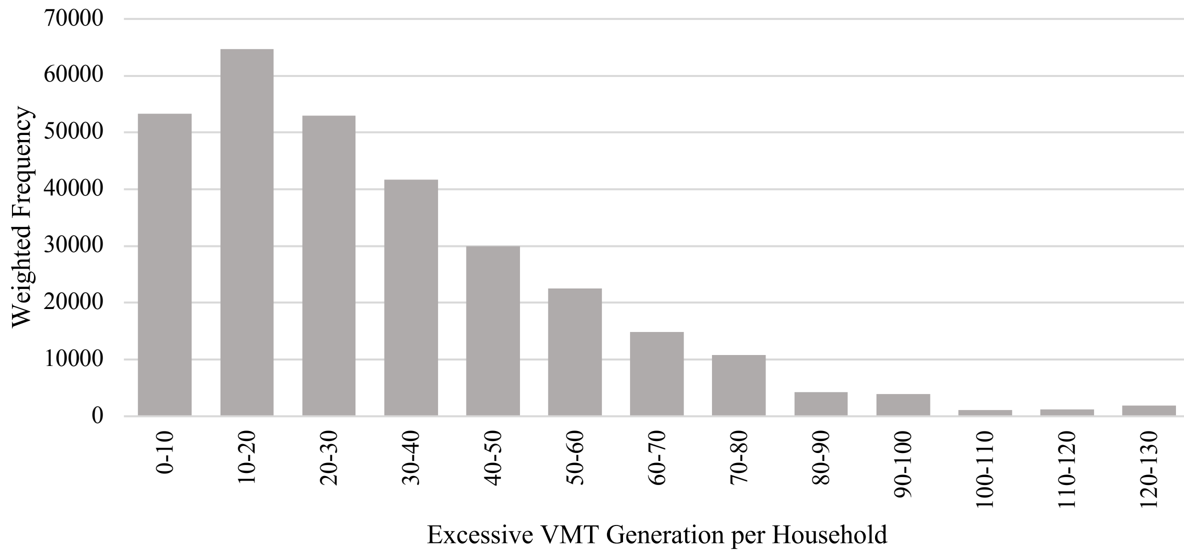

FIGURE 1 Histogram of excessive VMT generation per household (weighted)

The VMT generation for households that can reduce vehicle ownership will increase by 59.5%, on average, compared with current generation patterns (i.e. 50.1 VMT per household per day). The total VMT generation in the metropolitan area will rise by 13.3%, due to empty private AV relocation. Some other factors, which are not modelled in this study, may inflate the empty VMT generation in the future, including, but not limited to, cruising for less expensive parking spaces, activity rescheduling, and changes in travel patterns.

The temporal distribution of the excessive VMT indicate that the increase is the most significant during peak hours and hours during daytime, see Figure 2**.** The absolute increase in VMT is the highest during 4-6pm, with more than 1.1 million VMT added into the network per hour. During daytime (i.e. from 11 AM to 4 PM) the VMT generation increases by over 20%, which is the largest percentage increase throughout the day.

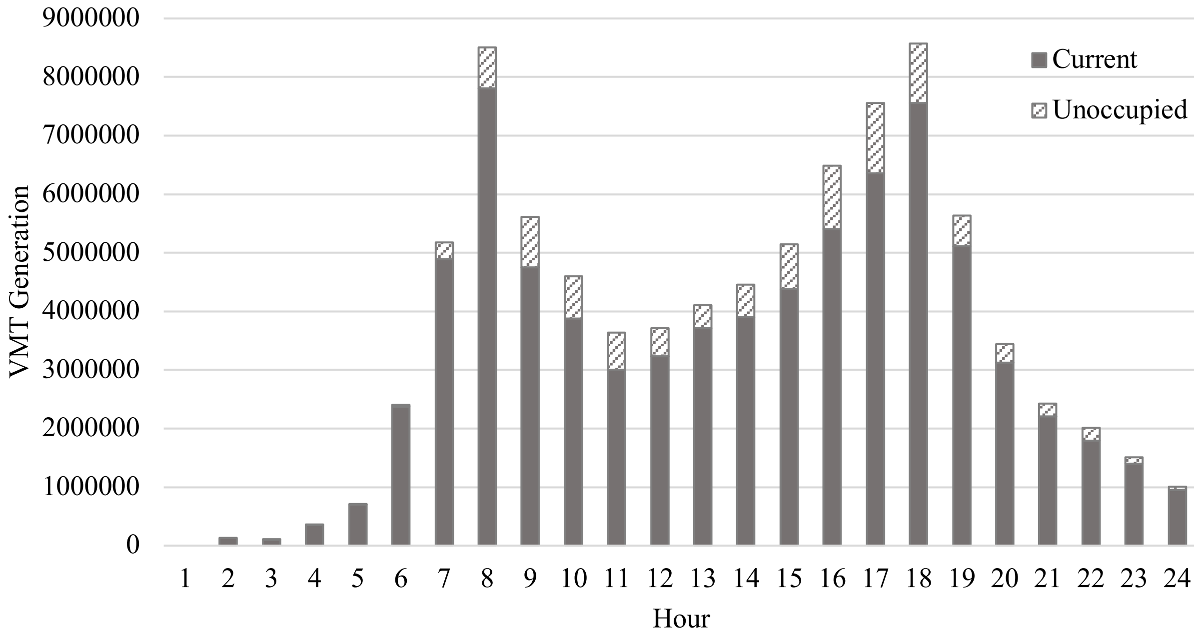

FIGURE 2 Temporal distribution of unoccupied VMT

Spatial Distribution of Excessive VMT

The spatial distributions of unoccupied VMT by time of day are estimated by applying the vehicle reduction and AV route optimization algorithm to the synthesized trip profile from ARC's activity based model. OD matrices of all empty AV relocation trips are generated by time periods: early morning (EA), morning peak (AM), midday (MD), evening peak (PM), and night (EV). New OD matrices are then generated by combining the current OD matrices with the relocation OD matrices. Trips assignments are implemented in CUBE, using the new OD matrices and local network. The trip assignment results provide updated traffic volume for each road segment, based on which the Volume-to-Capacity (V/C) Ratio are re-estimated. It is assumed that road capacity will remain unchanged, as the objective of this study is not to explore whether the roads will be more congested or not, but to obtain an understanding of the spatial distribution of unoccupied VMT in the region.

The changes in average V/C Ratio before and after the introduction of private AVs by location of road segments are shown in Table 2. In the early morning, the V/C Ratio only increases slightly, due to small travel demand at the beginning of the day. During this time of the day, excessive VMT tend to locate primarily in suburban, exurban, and rural residential neighborhoods. This may be due to the fact that the majority of the urban residents live in car-oriented suburban communities in Atlanta Metropolitan. These communities tend to generate some morning errands that may lead to extra unoccupied VMT generation. During morning and evening peak hours, the V/C Ratio, on average, increases significantly by around 7.99% and 8.44% respectively. The suburban, exurban, and rural neighborhoods, as well as urban commercial zones are more likely to experience the most dramatic increase in the V/C Ratio. This indicates that a large amount of relocation VMT is generated between commercial zones and residential zones after the adoption of PAVs. Therefore, the larger the mismatch between work and residential locations, the larger the overall relocation VMT generation will be in the future. Currently, a majority of commuters live in suburban residential zones and work in the urban core area. Atlanta is a typical monocentric city, rendering a large amount of empty relocation trips between commercial zones and suburban neighborhoods outside of the perimeter (I-285). Additionally, the results also indicate that the V/C Ratio increases the most during the midday period, when more PAV coordination will take place among household members. However, the midday traffic condition will not be as congested as morning and evening peak hours, as the overall V/C Ratio is still substantially lower during midday compared to peak hours. During night time, the V/C Ratio in the region increases by approximately 6.79%. The traffic volume inflates the most on road segments in suburban residential and exurban areas during night, due to relocations among non-work-related household activities in the evening.

In sum, road segments located in suburban, exurban and rural areas will experience higher percentage of increments in traffic volume after the coming of PAVs. This result is consistent with the logistic regression results, indicating suburban households are more likely to reduce vehicle ownership. However, roads in CBD and urban areas will remain more congested than other areas in the region, given the higher V/C Ratios throughout the day. Cities with more segregated land use may experience a higher percentage increase in the V/C Ratios in the future.

TABLE 2 Changes in V/C Ratios before and after AVs by Area Types

Time Period	Scenarios	CBD	Urban Commercial	Urban Residential	Suburban Commercial	Suburban Residential	Exurban	Rural	Overall
EA	BAU	0.104	0.105	0.104	0.100	0.092	0.075	0.063	0.094
	AV	0.105	0.106	0.105	0.101	0.093	0.076	0.064	0.095
	Changes	0.73%	0.90%	0.86%	0.98%	1.25%	1.24%	1.28%	1.07%
AM	BAU	0.398	0.417	0.411	0.376	0.337	0.234	0.165	0.343
	AV	0.415	0.446	0.439	0.406	0.367	0.253	0.177	0.371
	Changes	4.29%	7.03%	6.87%	8.09%	8.98%	8.18%	7.17%	7.99%
MD	BAU	0.368	0.358	0.334	0.297	0.255	0.166	0.124	0.269
	AV	0.391	0.392	0.362	0.326	0.283	0.183	0.135	0.295
	Changes	6.28%	9.54%	8.35%	9.74%	10.71%	10.41%	9.51%	9.75%
PM	BAU	0.473	0.493	0.484	0.443	0.400	0.281	0.201	0.408
	AV	0.503	0.540	0.523	0.486	0.441	0.307	0.217	0.447
	Changes	6.51%	9.38%	8.07%	9.87%	10.14%	9.20%	8.10%	9.44%
EV	BAU	0.201	0.225	0.220	0.209	0.190	0.129	0.098	0.183
	AV	0.211	0.240	0.233	0.223	0.204	0.139	0.104	0.195
	Changes	4.77%	6.55%	5.76%	6.90%	7.45%	7.50%	6.04%	6.79%

* BAU: Business as Usual

The changes in V/C ratios by types of road segments are shown in Table 3. The results from all time periods suggest that the majority of unoccupied traffic volumes are loaded on minor arterial roads, where the V/C ratios surge dramatically regardless the time of the day. During morning and evening peak hours, the V/C ratios inflate by 4.99% and 4.39% on expressways correspondingly, second to minor arterials. While during off peak hours (except for early morning hours), the V/C ratios rise more on principal arterials rather than expressways. These suggest that the relocation trips during midday and night time are shorter local trips compared with relocation trips incurred during peak hours. The average length of relocation trips declined from 18.5 miles during peak hours to 15.6 miles during off peak hours.

TABLE 3 Changes in V/C Ratios before and after AVs by Road Types

Time Period	Scenarios	Interstate / Freeway	Expressway	Parkway	Principal Arterial	Minor Arterial
EA	BAU	0.297	0.171	0.169	0.124	0.098
	AV	0.298	0.172	0.169	0.125	0.099
	Changes	0.31%	0.68%	0.29%	0.50%	1.00%
AM	BAU	0.650	0.514	0.549	0.468	0.375
	AV	0.669	0.539	0.564	0.486	0.403
	Changes	3.02%	4.99%	2.76%	3.73%	7.53%
MD	BAU	0.503	0.404	0.367	0.353	0.280
	AV	0.516	0.421	0.383	0.37	0.305
	Changes	2.65%	4.13%	4.15%	4.93%	9.16%
PM	BAU	0.692	0.557	0.554	0.547	0.440
	AV	0.709	0.581	0.576	0.573	0.479
	Changes	2.40%	4.39%	4.05%	4.71%	8.68%
EV	BAU	0.441	0.298	0.321	0.239	0.197
	AV	0.449	0.306	0.33	0.249	0.21
	Changes	1.86%	2.66%	2.83%	4.00%	6.83%

* BAU: Business as Usual

The intra-zonal relocation trips (i.e. trips that start and end in the same traffic analysis zones) are not loaded on the transportation network, as local roads are not included in the ARC's activity based model. In this study, we analyzed the impact of relocation trips on local roads by examining the density of intra-zonal relocation trips at the TAZ level. Figure 3 illustrates the spatial distribution of intra-zonal relocation trips density by time of the day. The number of intra-zonal relocation trips peaks during midday at over 1.41 million trips. The amount of intra-zonal relocation trips is 1.37 million during evening peak hours, which is slightly less than the amount incurred during midday. However, the spatial distribution of intra-zonal trips varies significantly during midday and evening peak hours. During midday, most of the intra-zonal trips are located in commercial zones adjacent to expressways in the region, indicating that the local roads in the commercial zones may experience a larger percent of increase in the R/C Ratio after the adoption of PAVs. On the other hand, the majority of intra-zonal relocation trips sprawled into suburban commercial and residential zones, which are further away from the expressways, during evening peak hours, suggesting local roads in suburban residential and commercial zones may witness a larger increase in R/C Ratio.

These results indicate that the generation of short (intra-zonal) relocation trips follows the trip generation patterns and location of work and residential places in the region. During the noon, more intra-zonal relocation trips are generated in the commercial zones in the region to serve work-based trips among household members. While, during night, a significant amount of relocation trips is likely to be generated to support household members to run evening errands. The results also indicate that zones with more mixed or diversified land use tend to have larger amount of intra zonal relocation trips. To alleviate future traffic pressure on local roads in these areas, designated dropping off and picking up stations may be considered to promote walking and reduce empty cruising.

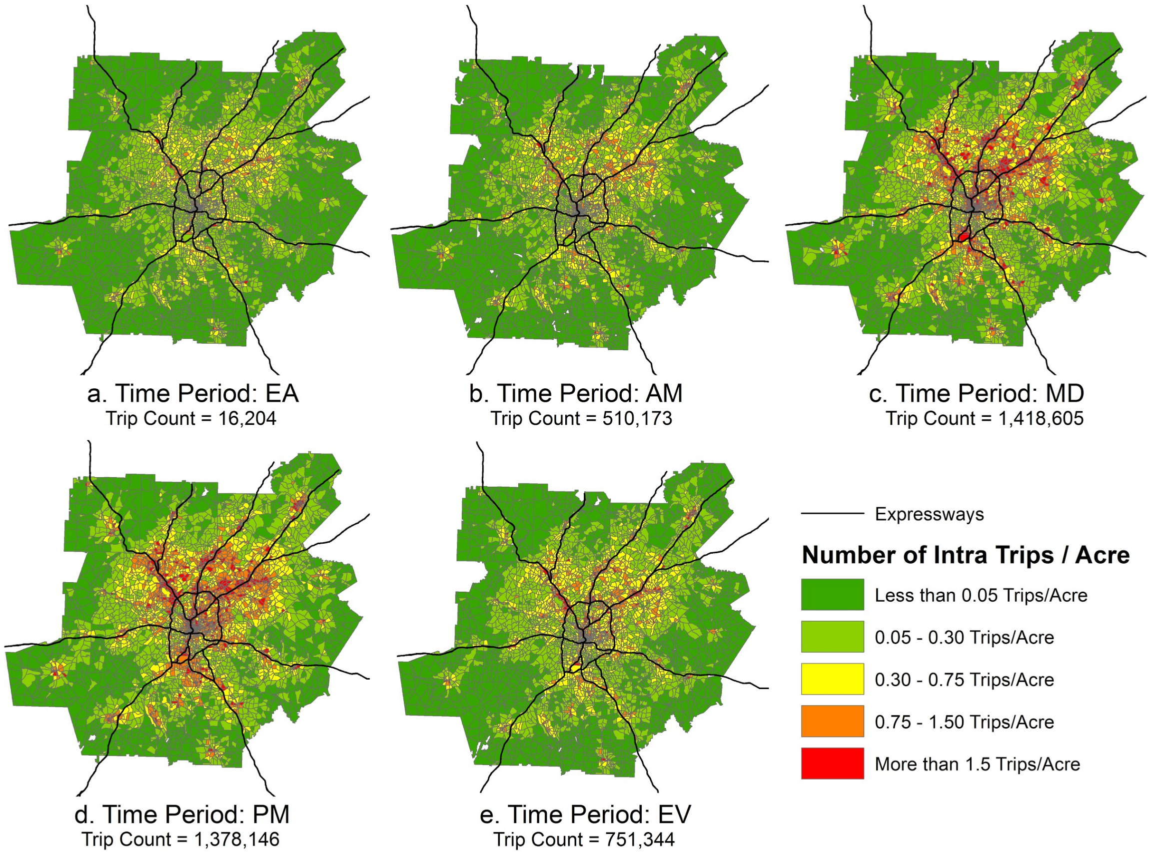

FIGURE 3 Spatial distributions of intra-zonal trips by time of the day

SCHEDULE FLEXIBILITY SENARIOS DEVELOPMENT

The above experiments are conducted based on the assumption that individuals do not have flexible activity schedules. In this section, we relaxed such assumption to determine how the results may vary if household members collaborate closely to reduce vehicle ownership. In the elasticity tests, we allow individuals to be dropped off 5, 10, and 15 minutes later than the current arrival time and results are tabulated in Table 4. As expected, more households can reduce vehicle ownership if delays are allowed. The percent of households that can reduce vehicle ownership increases from 18.3% to 24.1% when the activity schedules are relaxed by 15 minutes. The overall vehicle reduction rates also inflate from 9.5% to 12.3%. Moreover, marginal effects of schedule flexibility on vehicle reduction increases, as significantly more households can reduce vehicle ownership when the delay tolerance increases from 10 to 15 minutes compared with 5 to 10 minutes. The average vehicle ownership reduction, however, is quite stable across different tests. On average, households can only eliminate one vehicle regardless of schedule flexibility. The total VMT generation will also increase significantly when more households share PAVs among members. The results suggest that the schedule flexibility is also associated with excessive VMT generation at the household level. When no delays are tolerated the empty VMT per day per reduced vehicle is the lowest across all scenarios. The empty vehicle relocation VMT increases slightly first when 5 minutes of delays are tolerated and then declines when the schedules become more flexible. This is due to the fact that it is easier to optimize the PAV daily routes to reduce relocation VMT when larger delays are allowed. However, overall the relocation VMT still increases significantly due to more households are able to achieve vehicle ownership reduction and generate empty VMT.

TABLE 4 Flexibility Scenarios Results

Trip Delay Tolerance	No Delay	5 minutes	10 minutes	15 minutes
% HH Can Reduce Vehicle Ownership	18.3%	20.0%	21.7%	24.1%
Total Vehicle Ownership Reduction	9.5%	10.0%	10.9%	12.3%
Avg. Vehicle Ownership Reduction	1.089	1.099	1.104	1.112
Total Empty VMT Generation	13.3%	14.6%	15.7%	17.3%
Empty VMT per Day per Reduced Vehicle	29.8	30.7	30.6	30.2
Median Relocation Length per HH (Miles)	26.5	27.1	27.0	26.5

CONCLUSIONS

In this study, we developed a greedy algorithm to examine vehicle ownership reduction potentials after replacing private conventional vehicles by AVs. We also formulated MIP problems to minimize the AV relocation VMT and optimize AV routes, while fulfilling all households travel demand. After applying the models to the Atlanta metropolitan area, we found that even if consumers do not change the existing travel pattern, approximately 18% of the households can reduce vehicle ownership. If the schedule is relaxed by 15-minute time windows (i.e. arriving at destination 15 minutes after the current arrival time is allowable) up to 24.1% of the households are likely to at least eliminate one of the current private vehicles. The logistic regression model results show that higher income families, who live in suburban neighborhoods and generate more shorter trips, are more likely to be able to reduce vehicle ownership once PAVs are adopted.

In return for vehicle ownership reduction, a significant amount of unoccupied VMT will be generated in the region. For households who can reduce vehicle ownership, approximately 29.8 unoccupied VMT are generated per day per reduced vehicle. In the region, total VMT will increase by at least 13%. Such increase only includes unoccupied VMT generated during the vehicle relocation process. Other excessive VMT, such as cheaper parking lots cruising VMT, changes in travel behaviors (destination selection), will inevitably inflate the estimation. The majority of the occupied VMT occurs during evening peak hours. The spatial distribution patterns of the excessive VMT indicates that regions with more disaggregated land use patterns, especially larger mismatch between work and residential zones may experience larger VMT increases in the future in the PAV dominated future. Finally, most short intra-zonal repositioning trips take place in midday, which leads to larger percentage increase in the V/C Ratios during midday.

The designed and implemented models can be used as pioneering tools to analyze the vehicle ownership reduction and unoccupied VMT generation potentials in the era of PAV. The results of this study can inform policy makers regarding the challenges of PAVs, if widely adopted in the region, on existing transportation infrastructure, so that adaptation policies can be drafted to prepare for the coming of AVs. Such policies may include travel demand management tools, such as unoccupied VMT fees during peak hours to alleviate pressures on existing infrastructures and the design of dedicated AVs lanes to improve road capacity on expressways, where most of the unoccupied VMT are loaded.

While our results offer new understanding regarding regional light duty vehicle inventory and unoccupied VMT generation after the coming of PAVs, there are several aspects that merit future research efforts. Our models are developed based on the assumptions that travel behaviors, such as the trip generation rates, the choice of destinations, and the travel schedules of household members, will not vary significantly in the future. To gain more understanding regarding VMT generation, future efforts may employ stated preferences survey to examine evolving trends in travel behaviors. There has already been a wealth of literature regarding how different business models of AVs, especially the Shared AVs (SAVs) will influence regional vehicle inventory and VMT generation. It is critical to synthesizing current understandings to draw a comprehensive picture regarding how different market penetration of various business models of AVs will influence travel demand and consequently travel energy consumptions in the future. Last but not least, more regional attitude surveys should be conducted to characterize early adopters' socio-demographics and economic features to understand potential AV adoption trajectories, especially the adoption rates of PAVs, SAVs, and Transit Complementary AVs in the future. This information can provide critical guidance to plan for AVs during the transition period, which is not examined in this study.

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