Heaven or Hell: What are the life-cycle GHG emission implications for light-duty vehicles of autonomy and ridehailing?

Jennifer Hatch[1]
Will Gorman[2]

ABSTRACT. As has been well documented, the transportation sector is currently undergoing a profound transformation in the way that vehicles are powered, owned, and operated (Center for Automotive Research, 2016; Fagnant and Kockelman 2015; Sperling, 2017; Lovejoy, Handy, and Boarnet, 2013; Arbib and Seba, 2017). The complex interdependence of these transformations, as well as the fact that we are studying them concomitantly with their development, makes them particularly difficult to predict. Recent studies have shown preliminary evidence that ridehailing has shifted travel miles dramatically away from traditional forms of transport such as public bus and rail service, biking, and walking, and towards ride hailing services, resulting in a significant increase in VMT (Clewlow and Mishra, 2017). Building upon the model framework developed by Fox-Penner, Gorman, and Hatch (Fox-Penner, Gorman, and Hatch, 2018), this paper considers the greenhouse gas implications of various light-duty transportation adoption scenarios, including the effects on manufacturing inputs, technology improvements, total vehicle miles traveled, and the variation in emissions from an autonomous future dominated by internal combustion vehicles versus one dominated by autonomous electric vehicles. The goal of the paper is to build a more realistic and research based estimate of future transportation scenarios and the climate emissions impacts of the diffusion of autonomous technology with and without electrification.

KEYWORDS. Autonomous vehicles, greenhouse gases, ridehailing, life cycle analysis

1. Introduction

As has been well documented, the transportation sector is currently undergoing a profound transformation in the way that vehicles are powered, owned, and operated (Cite papers from Sperling, Kockelman, Seba, Etc.). Electrification, ridehailing services, and autonomy, the "three revolutions" underway in transportation sector, will have significant impacts on everything from infrastructure to electricity systems, public health, and greenhouse gas emissions.

The complex interdependence of these transformations, as well as the fact that we are studying them concomitantly with their development, makes them particularly difficult to predict. In less than a decade, ridehailing companies such as Uber, Lyft, and Ola have gone from rareified taxi replacements to companies that have not only upended the cab service but have also caused a significant transportation mode shift. Recent studies have shown preliminary evidence that ridehailing has swung travel miles dramatically away from traditional forms of transport such as

[1] Research Fellow, Boston University Institute for Sustainable Energy, hatchj@bu.edu - Corresponding Author
[2] Ph.D. Program, Energy and Resources Group, University of California, Berkeley, Ca., gorman_will@berkeley.edu

public bus and rail service, biking, and walking, and towards ride hailing services, resulting in a significant increase in VMT.

These services threaten to become even more dominant as autonomous vehicle technology becomes market-ready. In just a few years, autonomous vehicles have gone from closely monitored test-drives to driving the streets of Arizona. In 2017, the dominant players in ridehailing in the United States, Uber and Lyft, both partnered with automakers to test autonomous vehicle technology in their ridehailing model. Having fleets of autonomous vehicles will lower transportation costs (Bauer et. al 2018), causing an even greater mode shift away from public transportation as public transportation infrastructure costs increase due to necessary upgrades and declining ridership, and autonomous technologies mature.

There is near-universal agreement that motor vehicles will ultimately be fully autonomous or self-driven (Arbib and Seba, 2017; Bansal & Kockelman 2016; etc.). There is, however, a cacophony of opinions as to when and how the autonomy revolution will occur and its implications for travel, the economy, and our built environment. Making planning and prediction even more complicated is the question of whether or not these new autonomous vehicles will be electric. Many scholars have attempted to quantify aspects of this transformation, including estimating increased vehicle miles travelled (VMT), energy (electric) demand, and city infrastructure needs (Fox-Penner, Gorman, and Hatch, 2018; others). Yet perhaps one of the largest implications of the coming transformations has yet to be sufficiently bounded: the effect on GHG emissions as a result of the transformation. The future of autonomous vehicles is often assumed to be electric; however, current autonomous vehicle development has relied on internal combustion engine (ICE) technology.

Building upon the model framework developed by Fox-Penner, Gorman, and Hatch (Fox-Penner, Gorman, and Hatch, 2018), this paper examines the greenhouse gas implications of several potential scenarios for the future of transportation, considering varying degrees of adoption of autonomy, ride hailing, and electrification, with hopes of building a more realistic and research based estimate of the future for personal vehicle emissions.

To provide these estimates, we first conduct an extensive literature review of parameters affecting the GHG emissions from the light duty vehicle (LDV) sector, including impacts from autonomous vehicles. This review includes an assessment of the LCA literature to incorporate upstream emissions. Then, we develop a modelling framework that incorporates LCA parameters, vehicle adoption projections, stock modeling, efficiency improvements, and vehicle mile demand projections. From this modelling framework, we design the key scenarios that can be used to predict a range of outcomes for greenhouse gas emissions from autonomous vehicles. The full article will include detailed analysis following the outline below:

1. Introduction
2. Methods
   2.1 Model Description

2.2 Parameters affecting GHG Emissions from Autonomous Vehicles
2.2.1 Review of AV and drivetrain technology synergies and manufacturing emissions
2.2.2 LCA and manufacturing emissions
2.2.3 Vehicle adoption projections
2.2.4 The Impacts of Autonomy on VMT and EI
2.2.5 The Impacts of Sharing, Pooling, and Ridehailing on VMT
2.3 Scenarios
2.3.1 High EI ICE Autonomy
2.3.2 Low EI ICE Autonomy
2.3.3 High EI EV Autonomy
2.3.4 Low EI EV Autonomy
3. Results and Implications

2. Methods

2.1. Model Description

Our approach to integrating the various parameters described above into our model of GHG emissions from various autonomy scenarios is based on the work of Fox-Penner, Gorman, and Hatch (Fox-Penner, Gorman, and Hatch, 2018). In their paper they use an expanded Kaya identity to measure total electricity consumption in the light duty vehicle sector. For this paper, we augment this approach by including an emissions factor for manufacturing emissions and expanding our framework to incorporate a more detailed modelling of internal combustion engine drive changes so that we can more accurately capture LDV sector wide GHG emissions. The formula is shown below:

$$\sum_i [k_{i,t} * v_{i,t} * e_{i,t} * g_{f,t}] = \Phi_{l,t} \qquad (2)$$

where the stock in year t of light duty vehicles of a motorized vehicle type i is denoted by $\kappa_{i,t}$, $v_{i,t}$ is the average miles travelled by that vehicle type in year t, $e_{i,t}$ is the average energy use of the vehicle type i per mile travelled during year t, which we refer to as energy intensity (EI) (Kaya, 1990; Fox-Penner, Gorman, and Hatch, In Review), and $g_{f,t}$ is the emissions factor of type f (gasoline or electricity) in year t. This framework allows us to treat electric, hybrid, and non-electric autonomous cars all separately, adjusting energy use intensity and emissions profile for vehicle type as well as allowing the composition of the fleet to migrate from one type to another.

We use the model outlined above to integrate the numerous degrees of freedom introduced in the introduction of this paper, with the end goal of calculating the potential greenhouse gas implications of light duty vehicle transportation considering the effect of the three revolutions. Below, we summarize the literature we rely on to fill out the key parameters used in our model.

2.2. Parameters

2.2.1 Review of AV and drivetrain technology synergies and manufacturing emissions

2.2.2 LCA and manufacturing emissions

2.2.3 Vehicle adoption and LDV Stock projections

Our projection of LDV stock first begins with estimates of LDV stock from our prior work (Penner et. al.). First, we forecast electric vehicles sales using industry projects combined with a reduced form of the Bass Diffusion Model to model product growth rates. The specific quantitative formulation is shown below:

$$S_{(t)} = m\left(\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}}\right) \qquad (3)$$

Where,
S(t) = percent of total sales in year t
m = final percent of total sales
p = coefficient of innovation
q = coefficient of imitation
t = year

Next, we added a layer that estimated AV adoption. While there is a wide range of opinions as to when level 4 or 5 autonomous vehicles will become ubiquitous, some predict that shared CAVs will handle 95% of all passenger-miles by 2030 (Arbib & Seba, 2017) while others predict 100% level 5 autonomy will not occur until 2070 or later (Litman, 2017; Niewenhuijsen, 2015). Researchers also predict a wide range of scenarios or narratives as to how the CAV market will unfold (Shladover, 2015), (Niewenhuijsen 2015), (Lang, et al, 2016). Given these considerations, we adopt Lavasani, Jin, and Du's (2016) estimates of Bass or "S-curves" using parameters selected by comparing CAVs to other types of technologies (similar and dissimilar) for which there are full adoption histories (Lavasani, Jin, & Du, 2016). The results of Lavasani, Jin, and Du's base estimate is that cumulative CAV sales rise from 1.3 MM in 2030 (five years after introduction) to 70 MM by 2045 and saturation by 2060.

A significant assumption by many in the industry is that these vehicles will uniformly be electric. However, By allowing flexibility in our model design, we can thus evaluate future scenarios where AVs do not just start with the more environmentally benign electric type. As we explain below, such scenarios could have devastating consequences on reaching many of the GHG reduction goals for the LDV sector.

Our final augmentation over prior modelling efforts involves developing a more appropriate module to incorporate a future with large shared autonomous electric fleets. While this effort has only small (though significant) effects on the overall VMT demand in the LDV sector, it results in a significantly smaller stock of vehicles which is important considering our effort to analyze upstream emissions issues that result from vehicle manufacturing. To do this, we use assumptions from literature that suggest that for some number of personally owned vehicles, one SAEV could replace all of that travel demand. However, we acknowledge that these types of fleets are only likely going to be common in urban networks so limit the percentage of travel demand that can be served by such systems. With these assumptions, we reduce the total amount of LDV vehicle sales while holding overall VMT demand constant.

2.2.4 The Impacts of Autonomy on VMT and EI

2.2.5 The Impacts of Sharing, Pooling, and Ridehailing on VMT

3. Scenarios

Based on our review of the relevant parameters, we develop four key scenarios with various levels of adoption of autonomous and electric technology. These scenarios allow us to understand the dynamic implications of yearly changes in technology for total emitted CO_2 over the next 30 years.

Parameter	2020	2030	2040	2050
Ridehailing	Effect on Effect off			
EV/ICE Mix	Starts ICE Starts EV Migrates from ICE to EV Uses hybrid model	low turnover High Turnover No turnover	low High No	Low High No
AV VMT bump	Same as last paper			
AV EI timing (external)	Same as last paper			
AV penetration	High Low			
AV turnover/stock models		-Fleets -Individual ownership -Leasing/cell phone model		
Manufacturing Emissions	Linked to turnover			

EI (internal)	Linked to turnover			

1. Results/Conclusions and Implications

The timing of autonomous vehicle synergies with electrification matters. Climate change is becoming an ever more present and dire threat, and this exercise aims to highlight the significant differences in greenhouse gas effects stemming from the concomitant or independent development of autonomous and electric vehicle technology.

4. Acknowledgements

The authors gratefully acknowledge financial support from the Hewlett Foundation, the Energy Foundation, Boston University, and The University of California at Berkeley. We also thank a long list of experts who provided data and insights that were integral to this paper; please see a full list of acknowledgements can be found on our website at bu.edu/ise.

5. References

Aguirre, K., Eisenhardt, L., Lim, C., Nelson, B., Norring, A., Slowrig, P., & Tu, N. (2012, June). Lifecycle Analysis Comparison of a Battery Electric Vehicle and a Conventional Gasoline Vehicle. *Client: California Air Resources Board*.

Albright Stonebridge Group. (2016). *Autonomous Vehicles and Policy: Shaping the Future of Mobility*. Albright Stonebridge Group.

Alexander-Kearns, M., Peterson, M., & Cassady, A. (2016). *The Impact of Vehicle Automation on Carbon Emissions.* Center for American Progress.

Arbib, J., & Seba, T. (2017). *Rethinking Transportation 2020-2030.* RethinkX.

Auld, J., Karbowski, D., & Sokolov, V. (2016). Assessing the Regional Energy Impact of Connected Vehicle Deployment. *World Conference on Transportation Research.* Shanghai: Transportation Research Procedia.

Bank of America Merrill Lynch. (2017). *Thematic Investing: Overdrive - Global Future Mobility Primer.*

Bansal, P., & Kockelman, K. M. (2016). Are Americans Ready to Embrace Connected and Self-Driving Vehicles? A Case Study of Texans.

Barclays. (2015). *Disruptive Mobility: AV Deployment Risks and Possibilities.* Barclays Capital Inc.

Ciari, F., & Becker, H. (2017). How Disruptive can Shared Mobility Be? A Schenario-Based Evaluation of Shared Mobility Systems Implemented at Large Scale. In G. Meyer, & S. Shaheen (Eds.), *Lecture Notes in Mobility*. Springer International Publishing. doi:10.1007/978-3-319-51602-8_3

Davidson, P., & Spinoulas, A. (2015). *AUTONOMOUS VEHICLES - WHAT COULD THIS MEAN FOR THE FUTURE OF TRANSPORT?* Davidson + Spinoulas.

Ellingsen, L. A.-W., Majeau-Bettez, G., Singh, B., Srivastava, A. K., Valoen, L. O., & Stromman, A. H. (2013). Life Cycle Assessment of a Lithium-Ion Battery Pack. *Journal of Industrial Ecology*.

Ellingsen, L. A.-W., Singh, B., & Stromman, A. H. (2016). The Size and Range Effect: lifecycle greenhouse gas emissions of electric vehicles. *Environmental Research Letters*.

Fagnant, D., & Kockelman, K. (2015). Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers, and Policy Recommendations. *Transportation Research Part A, 77*, 167-181.

Greenblatt, J. B., & Saxena, S. (2015, July 6). Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nature Climate Change, 5*, 860-863.

Hawkins, T. R., Singh, B., Guillaume, M.-B., & Hammer Stromman, A. (2012). Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology, 17*(1).

Kim, H., & Wallington, T. (2016). Life Cycle Assessment of Vehicle Lightweighting: A Physics-Based Model to Estimate Use-Phase Fuel Consumption of Electrified Vehicles. *Environmental Science and Technology*, 11226-11233.

Kim, H., De Kleine, R., Wallington, T. J., McLean, H. L., & Luk, J. M. (2017). Review of the Fuel Saving, Life Cycle Emission, and Ownership Cost Impacts of Lightweighting Vehicles with Different Powertrains. *Environmental Science and Technology*, 8215-8228.

Kim, K.-H., Yook, D.-H., Ko, S.-Y., & Kim, D.-H. (2016). *An Analysis of Expected Effects of the Autonomous Vehicles on Transport and Land Use in Korea.* New York, NY: Marrion Institute, New York University.

Kockelman, K. M., Boyles, S., Stone, P., Fagnant, D., Patel, R., Levin, M. W., . . . Li, J. (2017). *An Assessment of Autonomous Vehicles: Traffic Impacts and Infrastructure Needs -- Final Report.* The University of Texas at Austin Center for Transportation Research.

KPMG. (2015). Connected and Autonomous Vehicles - The UK Economic Opportunity. Retrieved from https://www.kpmg.com/BR/en/Estudos_Analises/artigosepublicacoes/Documents/Industrias/Connected-Autonomous-Vehicles-Study.pdf

Laberteaux, K. (2014). *How Might Automated Driving Impact US Land Use?* Toyota Research Institute-North America; Toyota Motor Engineering & Manufacturing North America.

Lang, N., Rusmann, M., Mei-Pochtler, A., Dauner, T., Komiya, S., Mosquet, X., & Doubara, X. (2016). *Self-Driving Vehicles, Robo-Taxis, and the Urban Mobility Revolution.* The Boston Consulting Group.

Lavasani, M., Jin, X., & Du, Y. (2016). Market Penetration Model for Autonomous Vehicles Based on Previous Technology Adoption Experiences. *Transportation Research Record Journal*.

Litman, T. (2017). *Evaluating Public Transit Benefits and Costs: Best Practices Guidebook.* Victoria Transport Policy Institute.

Lovejoy, K., Handy, S., & Boarnet, M. G. (2013). *Impacts of Carsharing on Passenger Vehicle Use and Greenhouse Gas Emissions.* California Environmental Protection Agency Air Resources Board.

Martin, E., & Shaheen, S. (2011). The Impact of Carsharing on Public Transit and Non-Motorized Travel: An Exploration of North American Carsharing Survey Data. *Energies, 4*, 2094-2114.

Niewenhuijsen, J. (2015). Diffusion of Automated Vehicles. *A Quantitative Method to Model the Diffusion of Automated Vehicles with System Dynamics*. Delft University of Technology.

Norderlof, A., Messagie, M., Tillman, A.-M., Ljunggren Soderman, M., & Van Mierlo, J. (2014). Environmental Impacts of hybrid, plug-in hybrid, and battery electric vehicles -- what can we learn from life cycle assessment? *International Journal of Lifecycle Assessment*, 1866-1890.

Rodier, C., Alemi, F., & Smith, D. (2016). Dynamic Ridesharing: An Exploration of the Potential for Reduction in Vehicle Miles Traveled. *TRB 95th Annual Meeting.*

Samaras, C., & Meisterling, K. (2008). Life Cycle Assessment of Greenhouse Gas Emissions from Plug-In Hybrid Vehicles: Implications for Policy. *Environmental Science and Technology*.

Shaheen, S., Chan, N., Bansal, A., & Cohen, A. (2015). *Shared Mobility: A Sustainability and Technologies Workshop. Definitions, Industry Developments, and Early Understanding.* University of California Berkeley Transportation Sustainability Research Center and the California Department of Transportation.

Shladover, S. (2015). Automation Deployment Paths. Limiting Automation Functionality or Geographic Scope. *TRB Annual Meeting 2015 Session 564.* Washington.

Sivak, M., & Schoettle, B. (2015). *Influence of Current Nondrivers on the Amount of Travel and Trip Patterns with Self-Driving Vehicles.* Ann Arbor, MI: University of Michigan Transportation Research Institute.

Stephens, T., Taylor, C., Moore, J., & Ward, J. (2016). *Vehicle Technologies and Fuel Cell Technologies Program: Prospective Benefits Assessment Report for Fiscal Year 2016.* Argonne, IL: Argonne National Laboratory.

Underwood, S. (n.d.). *Automated, Connected, and Electric Vehicle Systems: Expert Forecast and Roadmap for Sustainable Transportation.* Dearborn, MI: Connected Vehicle Proving Center Institute for Advanced Vehicle Systems.

Walker, J., & Johnson, C. (2016). *Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services.* Rocky Mountain Institute.

Weis, A., Jaramillo, P., & Michalek, J. (2016). Consequential life cycle air emissions externalities for plug-in electric vehicles in the PJM interconnection. *Environmental Research Letters*. doi:10.1088/1748-9326/11/2/024009

Zhao, Y., & Kockelman, K. M. (2017). Anticipating the Regional Impacts of Connected and Automated Vehicle Travel in Austin, Texas.