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EXTEDNED ABSTRACT
Title: Will Vehicle Automation Accelerate or Decelerate Electrification: Modeling Demand for Automated Electric Vehicles

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INTRODUCTION

The emerging automated vehicle (AV) technology is shaping a new era in the future transportation world. There are concerns on how the AV technology will affect the future transportation energy. Although energy is not the original or biggest motivation for automation, it is of policy relevancy for mainly two possible energy impacts. AV could reduce energy consumption by improving fuel efficiency *(1)*, especially with connectivity technologies. AV can result in more vehicle sharing and ride-sharing, which can further improve vehicle occupancy and thus reduce the energy consumption *(2)*. On the other hand, AV could lead to higher energy use due to the rebound effect—i.e. travelers may travel more *(3)* or due to underserved consumers, including disabled, elderly, young children, people without a driver's license, and so on, joining the driver force. For example, every 1 in 5 people have a disability in the U.S. according to the Census report *(4)*, and many of them could not drive a vehicle.

A prior review study on AV technology *(1)* revealed that the AV technology may contribute to doubling vehicle miles traveled (VMT). Note that, doubling VMT also leads to doubling the current petroleum consumption by personal vehicles, an undesirable scenario hereby called "petroleum-based VMTx2" or "pVMTx2", unless the fleet share of efficient or clean fuel vehicles, such as electric vehicles (EV), is significantly increased. It has been argued that EVs are technologically more suitable for implementation of AV technologies *(5)*. However, technological compatibility does not necessarily mean that AVs will significantly accelerate the sale penetration of EVs. This is because if EVs still face barriers of high battery cost, uncertain battery ranges due to cold weather, limited charging infrastructure availability, and even safety risks with certain battery technologies, all these can carry over to automated EVs and prevent automated EVs from competing well against automated gasoline vehicles. Conceptually, it can be argued that automation can help mitigate some of the barriers to electrification. For example, the AV technology can support autonomously driving to a wireless charging pad, a task that is hard to achieve by a human driver *(6)*. Also, the AV technology can extend the electric range due to better fuel efficiency *(7, 8)*. However, the efficiency improvement from automation is also applicable for gasoline vehicles.

Therefore, how automation may improve the relative competitiveness of different fuel technologies is not yet clearly understood, but it is an important issue. If it is proved that automation will induce significant amount of travel demand and will not sufficiently stimulate the market share of clean fuel technologies (such as EVs), the next imperative questions are: should we accelerate the technology improvement of vehicle electrification and vehicle efficiency, for efficient and clean fuel technologies to outperform conventional gasoline vehicles before automation matures in the vehicle market? Or should we directly regulate fuel choices of automated vehicles, in order to prevent the "pVMTx2" outcome, such as the S.B.802 bill once pushed to California Assembly to require automated vehicles to be EVs?

The objective of this study is to develop a framework to quantify the relative effect – that is, to what extent and in what directions, will vehicle automation affect the market penetration of efficient and clean fuel vehicles in competing with gasoline vehicles?

METHODOLOGY

The market is viewed as a group of heterogeneous consumer segments, each choosing the perceivably least-cost choice from a given discrete set of vehicle powertrain technologies. Each consumer segment consists of a certain number of presumably homogenous households who share the same values of the pre-defined household attributes (e.g. driving intensity). The choice set includes a wide range of powertrain or fuel types and both human-driven vehicles (HVs) and AVs. The perceived generalized cost of each choice consists of both directly monetary cost components (e.g. vehicle price, lifetime fuel cost) and indirectly monetized cost components (e.g. generalized cost of range anxiety, generalized cost of reduced time cost or gained in-vehicle productivity from automated driving). Each cost component and therefore the generalized cost of a given choice are a function of attributes of both the choice and the consumer segment. The probability of a household of a given consumer segment choosing a given choice is higher when the generalized cost of the choice is lower. The correlation between the choosing probability and the generalized cost is assumed to follow the multinomial logit theory, where the unknown (or known but excluded) utility (linear conversion of the generalized cost) is assumed to be independent and identically distributed random variable that follows the generalized extreme value distribution. To capture inter-choice correlation, a nested multinomial model *(9)* is used. To capture heterogenous consumer preferences, consumer segmentation is carried out.

To reduce the effort, an existing consumer choice model that focuses on fuel types is adopted and expanded to include automated vehicles. This existing model is called Market Acceptance of Advanced Automotive Technologies model (MA3T) and the expanded new model is called MA3T-MobilityChoice or MA3T-MC. The existing MA3T model can predict HV sales and fleet size by four vehicle classes, 20 powertrain technologies, and multiple variants. For more details of the existing MA3T model, users can refer to studies *(10-12)*. The new MA3T-MC model is expanded with a more diverse choice structure that includes both HVs and AVs, additional technology attributes, and more detailed consumer segmentations by state, area, home type, vehicle ownership, driving intensity, commute distance, income and age.

To better reflect difference between HVs and AVs, insurance premium is used to reflect the potential safety benefits of AVs, and travel time cost is used to differentiate AVs and HVs.

A scenario called “1.1Cost0.7FuelUse” is constructed with the following assumptions:

- AVs are available on the market starting in 2030.
- AVs are initially 50% more costly than HVs, for each fuel type. The percentage decreases linearly over time to 10% in 2050.
- AVs are as efficient as HVs in 2030 and becomes increasingly more efficient than HVs over time. By 2050, AVs consume 70% of energy per mile as compared to HVs, for each fuel type.
- Other potential differences between AV and HV are ignored or assumed irrelevant to the fuel-automation interaction issue.

FINDINGS

Based on the simple assumptions of the “1.1Cost0.7FuelUse” scenario, sales shares by fuel type and automation are projected by MA3T-MC for the year of 2050. As shown in Figure 1, the sales share of conventional gasoline vehicles is more than doubled with automation, while hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs) suffer significantly. The fundamental reason is that equal percentages of efficiency improvement benefits inefficient vehicles more. For example, as shown with an example consumer segment (#26 in MA3T-MC) in Figure 2, the energy cost in net present value is $14,771 for a gasoline HV in 2050 and $10,340 for a gasoline AV, exactly a 30% reduction as a result of the scenario assumptions. This 30% reduction results in savings of $4,431 for this example consumer. The energy cost is $5,819 for a PHEV HV and $3,311 for a PHEV AV, a 43% reduction. It is higher than the 30% per-mile energy use reduction because some of the gasoline-powered miles traveled are now fueled by electricity, cheaper than gasoline, due to the automation-extended electric range. However, this higher percentage savings actually lead to a net saving of $2,508, much lower than the automation savings for gasoline conventional vehicles. This is why energy-efficient vehicles including HEVs and PHEVs lose market shares to gasoline vehicles as a result of the intervention of automation. This raises concerns of potentially more petroleum use and more emissions and is worth further studying.

One feedback to this study was that automation may impact vehicle efficiency to different extents by fuel type. It is generally believed that automation may improve the efficiency of gasoline conventional vehicle more than that of HEVs or PHEVs. It this is true, the finding, that the less efficient gasoline conventional vehicles may benefit more than HEVs and PHEVs from automation, can only be strengthened.

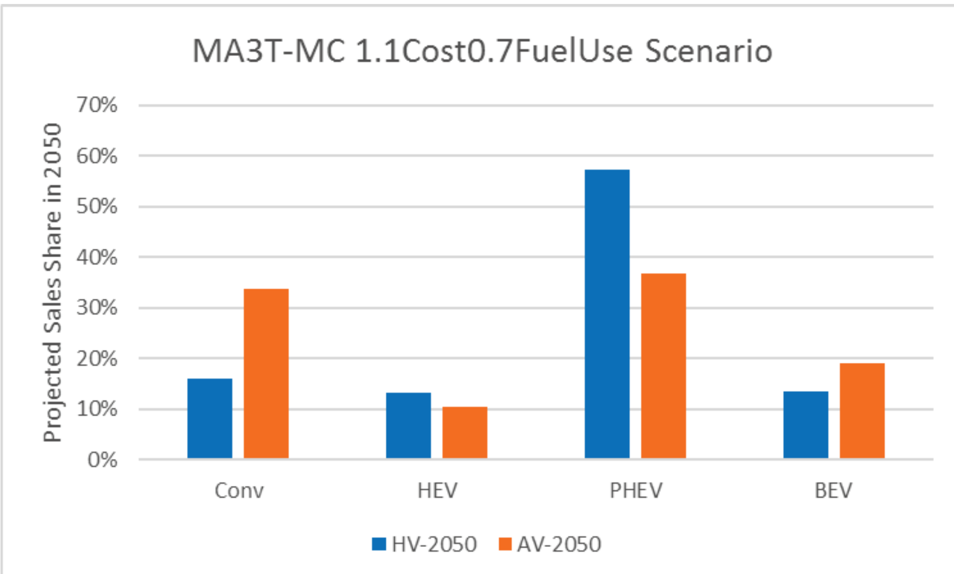

Figure 1. Projected sales share by fuel type and automation.

Interestingly, as seen from Figure 1, the sales share of battery electric vehicles (BEVs) increases from 13% among HVs to 19% among AVs. Energy cost is not the cause, as BEVs are also more efficient than gasoline vehicles and will not benefit as much on energy cost from automation. What makes automated BEV AVs more competitive than BEV HVs is less range anxiety cost (or called range limitation cost). The 30% reduction in per-mile energy use from automation is equivalent to an extension of the driving range by 1/0.7-1= 43%, without the extra capital cost to increase the battery capacity. This can be of significant value to some consumers. As shown in Figure 2, for a frequent driver at 21,208 miles driven per year, extending the driving range of a 100-mile BEV to 143 miles makes the 100-mile BEV range-feasible for 97% of days (up from 87% with a BEV HV). Assuming $50/day of penalty for each day the BEV is not range-feasible due to long distance driving *(15)*, the automation-enabled range extension is worth $1,825/year to the consumer. This is a significant value, explaining the sales share increase in Figure 1. Consumer heterogeneity must however be considered. Some consumers have certain driving patterns and intensities that will not benefit much from automation on range extension. As also shown on Figure 2, consumer #4 drives most of the time below 50 miles per day. The

43% range extension does not increase the range-feasible days and thus is of little value to this consumer.

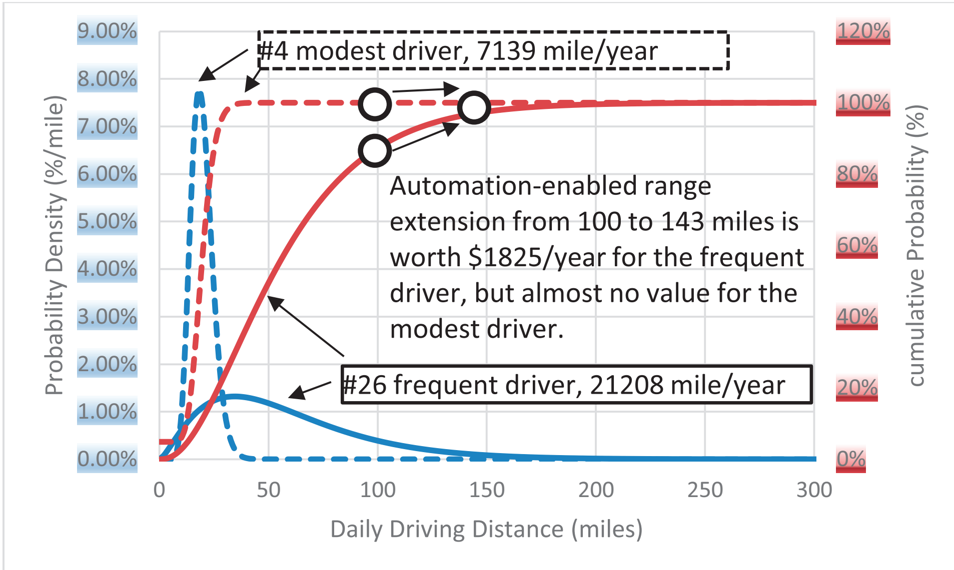

Figure 2. Value of automation-enabled range extension—2-driver illustration.

CONCLUSIONS

Automation may induce more travel demand, posing potential threats to energy security and environmental protection unless the induced travel demand is served with more efficient or clean fuel technologies. This study thus aims at whether automation may promote or discourage market penetrations of EVs. A consumer choice model called MA3T-MC is developed by expanding the existing MA3T model that focuses only on fuel type choices. Key findings include: 1) automation may increase sales shares of gasoline conventional vehicles and decrease shares of efficient vehicles including HEVs and PHEVs. 2) automation can increase market shares of BEVs, due to the "free" range extension from the efficiency improvement by automation. 3) consumer heterogeneity is important to quantify the national impact of automation on sales shares by fuel types and the total energy use.

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