

Modeling and analyzing near term transitions to alternative fueled vehicles using a spatial regional consumer choice and fueling infrastructure model

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Summary

This model provides an integrated framework of spatially detailed analysis of consumer choice with geographic specification of charging availability. This method is improved upon the traditional consumer choice modeling approach of representing aggregated regional infrastructure. The model uses nested multinomial logit approach for simulating a vehicle choice function with varying demographic and utility parameters across each zip code area, and thus different choice probabilities for specific vehicle technologies are determined. The model is built in R programming language and visualized using Leaflet, a JavaScript package.

1. Background

The adoption of battery electric vehicles in the market depends on a variety of technology and fueling infrastructure characteristics ranging from vehicle price (which includes the battery pack cost), effective range of the vehicle technology, availability of recharging infrastructure and so on. It is not possible to generalize consumers' reaction to these attributes when it comes to predicting vehicle purchase behavior of BEVs as their perception of the vehicles utility can vary based on their driving patterns, risk tolerance towards new technologies, and the charging infrastructure availability at home, work and in public locations. For example, limited access to charging infrastructure would likely limit their daily distance that can be driven depending on the vehicle's range, which might decrease the likelihood of the people in the region to buy BEVs, even if the vehicle and fuel costs are competitive with other vehicle alternatives. These non-monetary factors, therefore, cannot be ignored while considering consumer adoption of electric vehicles in the future.

These inconveniences or perceptions of consumers are traditionally quantified as additional costs in consumer choice models ([1], [2]), representing range limitation, limited infrastructure access, low make/model diversity, technology risk and so on. For instance, for a consumer who drives a significant number of miles annually, a lack of proper infrastructure access (work or home or public), can increase their 'disutility' or the non-monetary cost of their perception towards limited range electric vehicles.

Though these models capture the key barriers to vehicle utility based upon the perception of consumers of infrastructure availability, these models operate on a rather spatially aggregated level, typically nationwide ([1], [3]) which means, these models assume an additional charging station will be equally available to all the consumers in the nation. However, the convenience associated with charger availability is extremely local in nature and without spatial information, important details are lost in calculating the effect of infrastructure on the consumers. Our approach of a spatially disaggregated consumer choice model, where consumers are modeled at a very fine regional scale, is helpful to establish the relationship between important characteristics of consumers that vary by geography and their vehicle purchase choices.

2. Model Design

2.1. Model Structure and Methodology

The model structure consists of four main parts (shown in Figure 1): (a) input module that merges data sets to a consists of merged spatial database structure for each type of consumer at the zip code level, (c) compute module that calculates the relevant disutility costs for each consumer in a given location, which is sent to the core module, (c) nested multinomial logit module (NMNL) at the core, and (d) output module that visualizes the results through maps, and calculates the cost and carbon emissions. The structure of the nested multinomial logit module is obtained from the MA³T model, developed by Oak Ridge National Laboratory [4]. Each consumer segment in the model uses the NMNL core, which is a form of discrete choice model that clusters similar technologies as ‘perfect substitutes’ (shown in Figure 5) and determines the purchase probabilities of vehicle technologies for a given consumer based on the total cost of the vehicle technology (monetary and disutility costs).

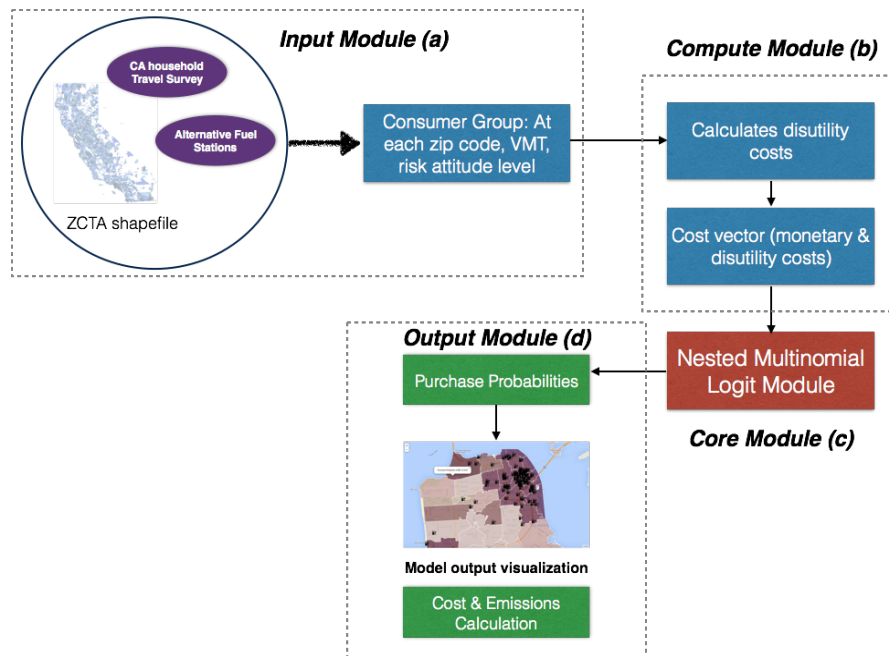


Figure 1: Spatial Consumer Choice Model Structure

The ‘infrastructure availability’ parameter is computed from the number of EV charging or hydrogen refueling stations relative to the number of gasoline fueling stations. The compute module

calculates the number of EV or H₂ stations per square mile, from the total number of charging stations or hydrogen refueling stations in the given zip code area and the zip code area. In order to get relative percentage, we initially assume that there are at least 4 gasoline stations per square mile in any given area. The ratio of alternative fuel stations per square mile to gasoline stations per square mile is defined as the infrastructure availability parameter.

The spatial structure of the model is constructed from various data sources. In this initial implementation, we are focusing on the details at zip code level. The alternative fuel station locations are obtained from Department of Energy's Alternative Fuels Data Center [5]. The zip code tabulation area shapefiles are obtained from US Census [6], which is used for calculating the station availability parameters and visualization of results. The vehicle-miles-traveled data is obtained from 2013 California Household Travel Survey [7]. This is a detailed set of travel survey data collected from different individuals on their daily driving behavior, as well as other household attributes. Each individual is identified by their sample ID, and their respective city name and zip code are provided in the data set. In this exercise, we are aggregating the daily driving miles into average annual miles traveled, and grouping them into different VMT categories (as shown in Table 1). Other important demographic attributes, such as, household income, number of family members, etc. from the data set will be included in the decision process in future model versions.

Table 1: Vehicle Miles Traveled Categories in the model

VMT Category	Average Annual Vehicle Miles Traveled (miles)
1	< 5000
2	5000 to 10,000
3	10,000 to 15,000
4	15,000 to 25,000
5	25,000 to 30,000
6	30,000 to 35,000
7	> 35,000

For each zip code tabulated area, we first create consumer segments based on the VMT categories (shown in Table 1). Then, we provide a constant variation of risk groups for each VMT category, i.e. the consumers are divided into three categories, early adopter, early majority and late majority, based on their risk perception towards new technologies, i.e. early adopters are the innovators who perceive the novelty of the technology as a positive utility, whereas late majority group perceives the newness of the technology as risk and would be less willing to invest in it. In any given group, the percentage of early adopter population is considered to be about 8%, early majority population constitutes 38% and the rest consists of late majority. This division is based on Oak Ridge National Laboratory's MA3T model assumptions which was derived from an aggregated definition of innovation diffusion curve [4]. Figure 2 shows the illustration of consumer segment divisions for each zip code area in the model. There are about 21 subdivisions (7 VMT groups X 3 risk groups) for each region. The NMNL core estimates purchase probability decisions for each sub-group, and the results are then aggregated at the zip code level, based on their weighted average of VMT and risk group shares. The infrastructure availability is constant for all the subdivisions in the zip code region as they denote public stations or public charging, but they vary across zip code areas. In this

model version, we assume the consumers do not have access to home or work charging, and rely only on public chargers, which will be incorporated in the later iterations.

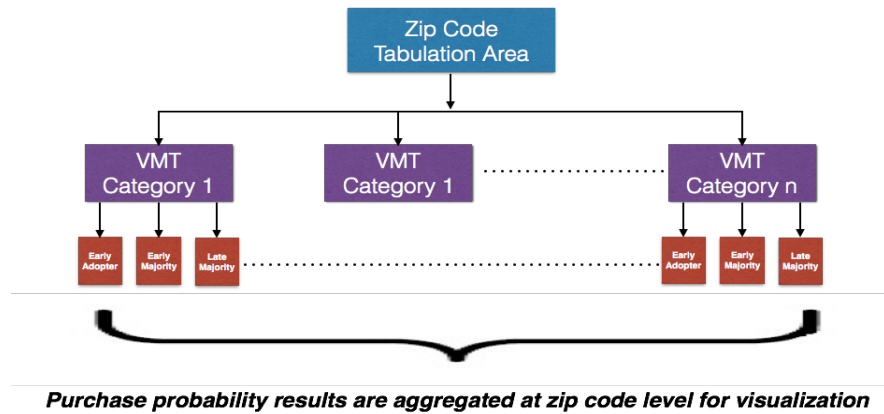


Figure 2: Consumer Segment Divisions at Zip Code Tabulated Area Level

Fuel prices are given exogenously in the model [8], which are used along with vehicle efficiency and annual miles of the consumer to estimate the fuel cost of the vehicle. We assume that consumers have limited perception of fuel cost when it comes to vehicle purchase, and they perceive only 5 years of fuel savings at the time of purchase. The refueling inconvenience and range limitation costs were estimated based infrastructure availability, annual miles driven, risk attitude (for range penalty), and other vehicle attributes (such as efficiency, storage, range).

This preliminary model computes purchase probabilities for any time period in which data is available. The model input has vehicle price and fuel price trajectories up to the year 2050, and the user is allowed to specify any year as input to obtain the purchase probabilities based on these price trajectories. However, our initial model only has a representation of current infrastructure availability, based on the existing stations and chargers, so this model is limited to near-term predictions (e.g. until the year 2020). The future versions of the model will include projections for fueling infrastructure deployment and the interactive effects of the previous years' vehicle sales trajectory, which would yield a better framework for long-term analysis.

2.2. Model Inputs and Cost Estimation

Our model includes vehicle prices, fuel costs as well as non-monetary “disutility” costs as part of the vehicle purchase decision process. The vehicle prices differ across the different technologies, and they do not vary across consumers. The annual cost a consumer spends on fuel may vary based on the their driving profile, vehicle efficiency and fuel prices. In addition to these costs, in this initial model implementation, we are considering the effect of infrastructure availability on the vehicle purchase behavior of consumers.

As mentioned earlier, infrastructure availability (such as access to public chargers) is a spatially sensitive parameter. Whether or not a consumer will have range limitation issues when it comes to adopting electric vehicles depends on their access to home and/or work and/or public chargers. Lower access to charging infrastructure will increase a cost component known as ‘range limitation cost’. This cost is calculated from a consumer’s effective daily range with a given electric vehicle, based on its battery capacity, efficiency and the consumer’s access to charging infrastructure. While calculating the electricity available (in kWh) from public chargers, an uncertainty parameter is included, called ‘public charging station availability’ expressed in percentage, which captures the probability of finding a charger when the consumer needs it. Low availability of chargers may be due to fewer public chargers in the region as well as the presence of charger congestion. The electricity available (in kWh) from the charging infrastructure

depends on recharging time as well as the type of charging infrastructure (Level I, II or fast chargers). Based on the daily VMT distribution of the consumer, if the vehicle is able to meet the day's demand, then the BEV is used for that day, otherwise it is assumed that a rental car is driven instead. A cost penalty (also called 'anxiety cost') is calculated for those days when rental car is driven. This anxiety cost can vary from person to person, based on their risk perception (e.g. early adopters have a lower anxiety cost than late majority people) [9]. Figure 3 shows an illustrative example on the variation of range limitation cost of EV 100-mile range car for consumers of different driving profiles, and how the range limitation cost decreases with increase in public charging availability. [Here, low annual VMT ~ 8600 miles, medium annual VMT ~ 16,000 miles, and high annual VMT = 28,300 miles].

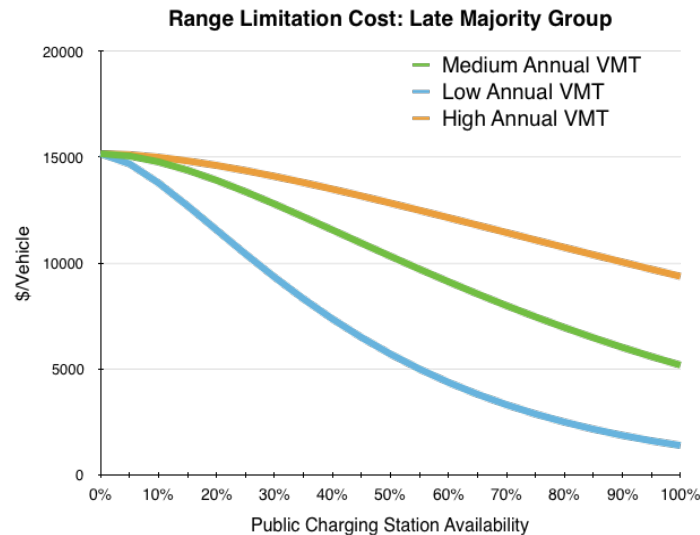


Figure 3: Range Limitation Cost for Battery Electric Vehicles for three driver groups

This infrastructure availability parameter also applies to fuel cell vehicles. In this case, the cost component is called 'refueling inconvenience cost'. This cost mainly depends on the driving behavior of consumers, fuel efficiency, and the vehicle storage capacity, from which, the number of annual trips to the refueling station is calculated. This value is multiplied with the cost of 'one refueling trip' (derived from wage rate, search time multipliers based on Ogden et al [10]). Figure 4 shows how the refueling inconvenience cost decreases with increase in station availability.

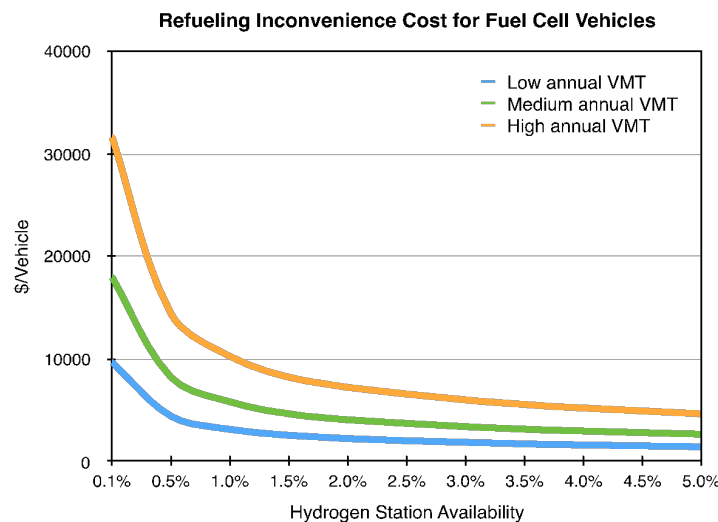


Figure 4: Refueling Inconvenience Cost for Fuel Cell Vehicles for three driver groups

In both these cases, the ease of infrastructure access is denoted by 'availability' expressed in percentage. It is assumed that drivers have no issue in finding a gasoline station, hence they have 100% availability at any given time. In the case of alternative fueled stations or chargers, a spatial estimation is done in a given area, based on the current chargers or hydrogen stations available in the area (explained in section 2.2).

The vehicle technologies used in the model is shown in Figure 5, where they are arranged in a 'nest structure', such that, similar technologies are clustered together. The nested multinomial logit module (NMNL) uses this structure to determine purchase probabilities. More details on the nest structure and the technical aspects behind the logit module can be found in Lin et al [3]. Vehicle price and efficiency graphs are shown in Appendix.

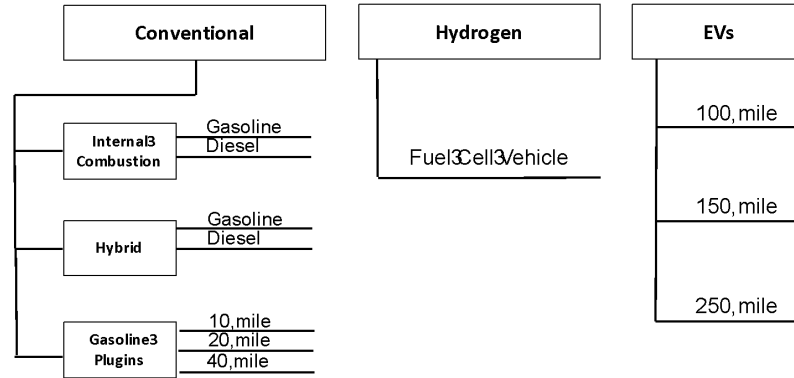


Figure 5: Vehicle Technologies in the model

2.3. Model Tools

The first three parts of the model are built using R programming language. The output module is visualized using Google Maps API, and the interactive maps are produced using Leaflet, an open source JavaScript library.

3. Preliminary Results

For the preliminary set of results, battery electric vehicle purchase probabilities are analyzed for the cities of San Francisco and Los Angeles based on the existing infrastructure data. San Francisco has 28 zip code tabulation areas and Los Angeles has 63 zip code tabulation areas. Table 2 shows the infrastructure availability parameters EV and H₂ stations for selected San Francisco and Los Angeles neighborhoods.

Table 2: Infrastructure Availability for selected neighborhoods in San Francisco and Los Angeles

City	Zip Code	Neighborhood	EV Station Availability	H ₂ Station Availability
San Francisco	94132	Lake Side	32.3%	0%
San Francisco	94102	Tenderloin	17.5%	0%
Los Angeles	90008	Baldwin Hills	70%	10%
Los Angeles	90033	Boyle Heights	7.5%	0%

Daily VMT distribution from individual samples of from California household travel survey is populated for each zip code region. Average annual VMT and VMT shares are then calculated from this data. Figure 6 shows the daily VMT distribution for selected zip code neighborhoods in San Francisco and Los Angeles regions.

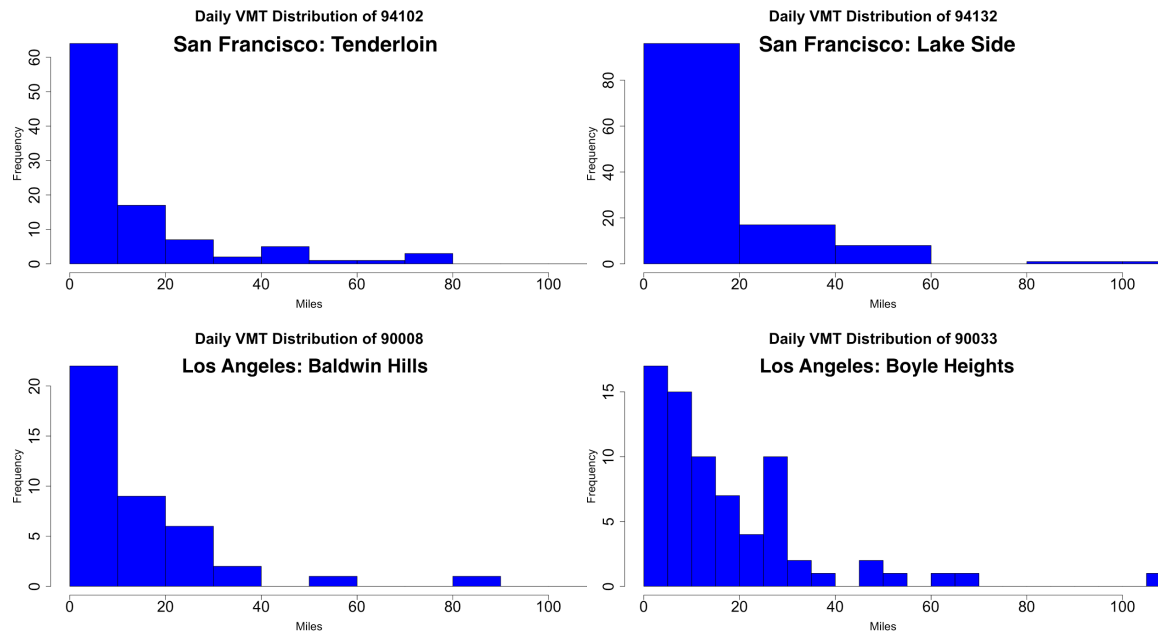


Figure 6: Daily VMT Distribution of selected neighborhoods in San Francisco and Los Angeles

As mentioned earlier, each zip code region has 21 consumer segments divided based on their driving profile and risk attitude. The compute module calculates the vehicle, fuel and disutility costs for each of the vehicle technologies in the choice set for each consumer segment, which is then used by the nested multinomial logit core module to estimate the purchase probabilities. Figure 7 shows the aggregated vehicle purchase probability of San Francisco and Los Angeles regions. We can observe that gasoline vehicles still dominate the market, followed by gasoline hybrids. The total market share of battery electric vehicles in San Francisco is about 6%, compared to 3.7% in Los Angeles. This could be due to the daily VMT distribution of the population in Los Angeles having higher annual miles driven on average compared to San Francisco (Figure 6). We can also observe the presence of fuel cell vehicle adoption in Los Angeles (0.5% of total market share), which is due to the presence of hydrogen stations in that area. It has to be noted that, the vehicle market shares presented in the figure is illustrative and produced from the limited current version of the model, and it does not include all the disutility cost components in its calculation, which may result in overestimation of certain vehicle technologies.

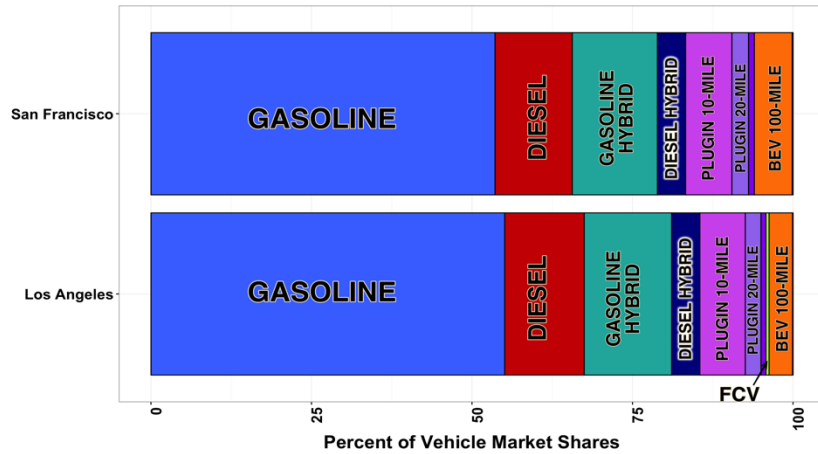


Figure 7: Market Share of all the vehicle technologies for San Francisco and Los Angeles

The results are then spatially disaggregated and visualized through thematic maps (referred to as choropleth maps, where the shading varies based on the value, in this case, high purchase probability areas are in dark shades). Figure 8 shows the choropleth map of BEV purchase probability amongst all the vehicle technologies in the city of San Francisco. The live link of this interactive map can be found [here](#). We can observe that consumers living near high concentration of public electric chargers have a higher battery electric vehicle purchase probability compared to the rest of the population.

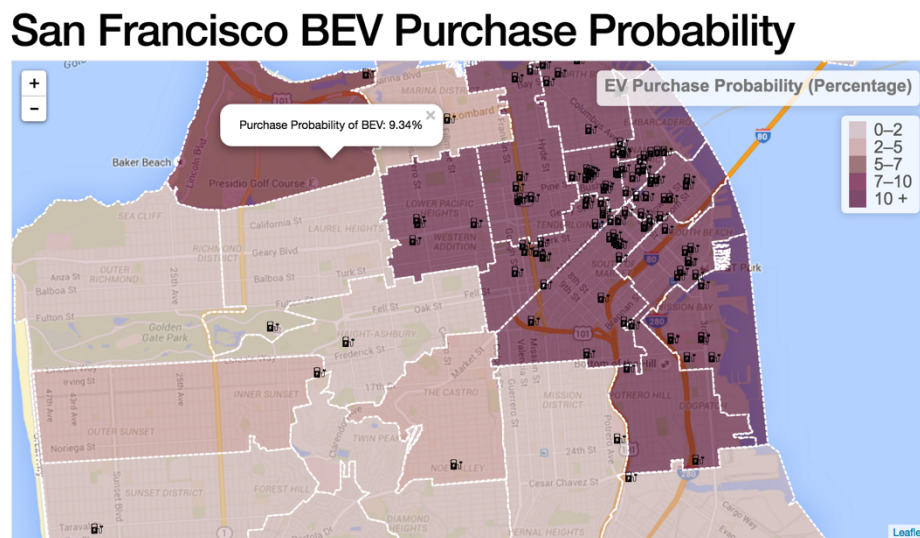


Figure 8: Illustration of live Choropleth Map showing Battery Electric Vehicle Purchase Probability in San Francisco

4. Summary

When consumers purchase a vehicle, they perceive non-monetary costs in addition of vehicle prices and fuel costs in their decisions. Vehicle consumer choice models capture these factors in two ways: by segmenting the consumer groups based on their characteristics, and by parameterizing their perception in the form of ‘disutility costs’. Consumer segmentation approach greatly helps in identifying certain consumer characteristics, such as, risk attitude, driver profile and so on, which influences the decision making of vehicle purchases. Traditionally, these choice models have ignored spatial sensitivity, and have used aggregated (average) values to predict vehicle purchase probability. Spatial characteristics form

another dimension of consumer segmentation, as they can bring in the socioeconomic data, income, travel behavior and other attributes to the model, which can add value. The spatial consumer choice model illustrates a methodology to use these spatial attributes to introduce a more refined layer of decision-making and provides a more realistic way of representing the heterogeneity among consumers. This preliminary version uses two disutility cost components: range limitation cost and refueling inconvenience cost estimated based on the coverage of stations and chargers in a given area. This is an important modeling improvement because it allows for a better representation of the effects of fueling infrastructure deployment on the adoption of alternative vehicles, such as battery electric vehicles. Understanding this relationship is critical for policymakers and policy design for increasing the adoption of cleaner vehicles. It also has important feedbacks to the geographic dispersion of vehicle purchase, which can in turn affect the business case for fuel infrastructure deployment and supporting infrastructure needs.

The results are visualized for San Francisco and Los Angeles regions. The future versions of the model will parameterize and incorporate spatial differences as disutility cost components for household demographics, such as, income, mode of travel, number of family members, home and work charger availability and so on, to refine the current methodology. Moreover, the current version of the model is time independent, i.e., the purchase probabilities can be estimated only for a given year, in this case, for the current infrastructure system. The model will be revised to include the interactive effects of previous years' vehicle sales, and scenarios will be run to estimate future vehicle purchase probabilities for different infrastructure investment patterns.

References

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Authors

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Kalai Ramea is a Ph.D. candidate in Transportation Technology and Policy program at University of California, Davis. Currently, she is working on incorporating consumer behavior in large-scale energy systems models for the light-duty vehicle sector, and studies how consumers interact with various infrastructure investment scenarios in order to meet climate target goals.



Dr. Christopher Yang

Christopher Yang received his Ph.D. in Mechanical and Aerospace Engineering from Princeton University. He is currently a research scientist working within the Sustainable Transportation Energy Pathways program at ITS-Davis and a Faculty member in the Transportation Technology and Policy graduate program. His research focuses on analysis of alternative fuels and advanced vehicles and their role in reducing transportation greenhouse gas emissions, with an emphasis on hydrogen and electricity supply and infrastructure.



Dr. Michael Nicholas

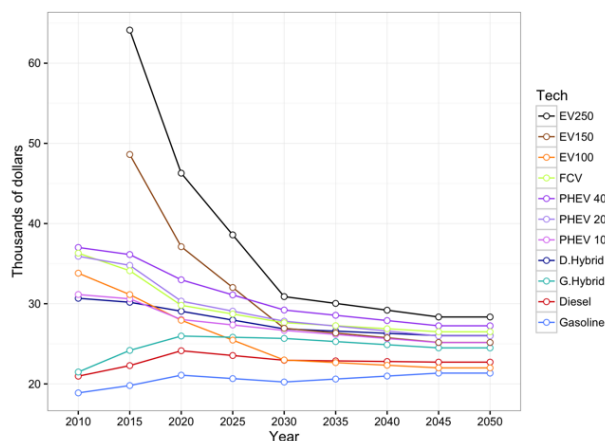
Michael Nicholas received his PhD in Transportation Technology and Policy from UC Davis. He is currently continuing his work as a postdoctoral researcher at UC Davis. He is leading researchers in the PH&EV Research Center constructing a GIS toolbox which will allow for a methodical approach to the understanding, planning and deployment of electric vehicle infrastructure.



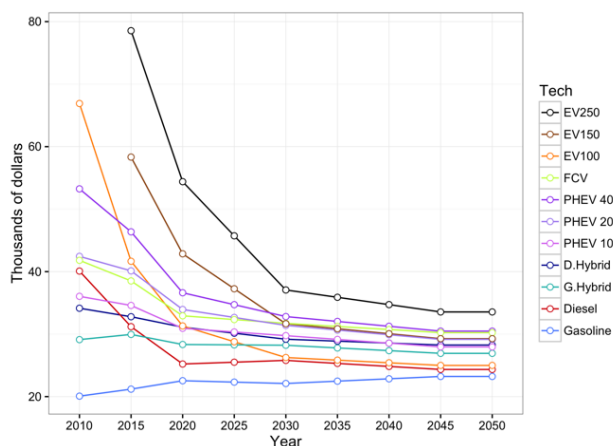
Appendix

Vehicle Prices

Light-duty cars



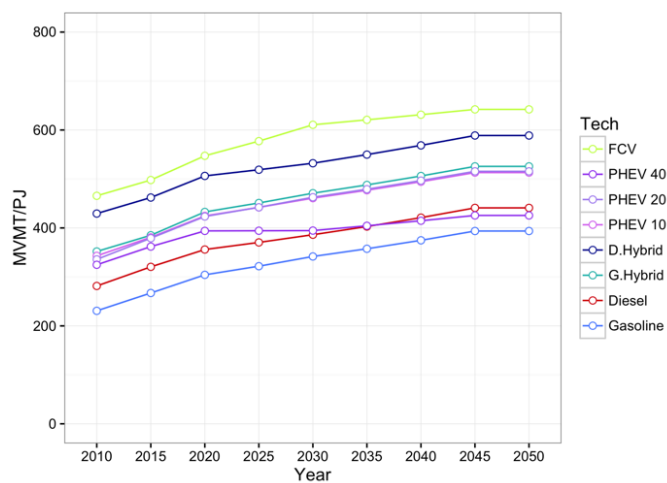
Light-duty trucks



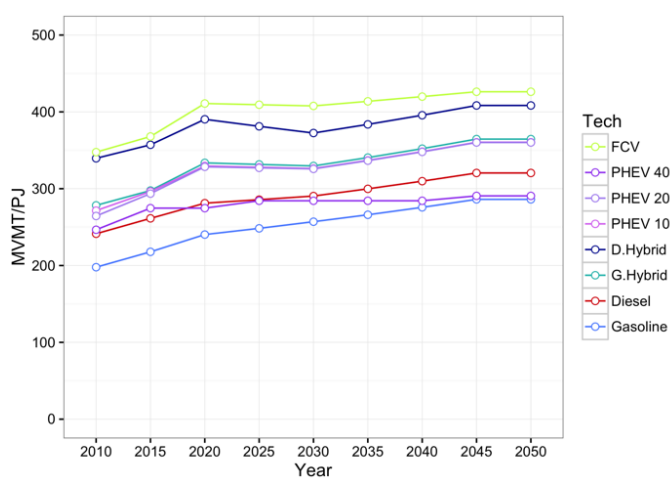
G.Hybrid: Gasoline Hybrid; D: Hybrid: Diesel Hybrid; PHEV: Plugin-Hybrid (10-mile, 20-mile and 40-mile range vehicles); FCV: Fuel cell vehicle; EV: Electric Vehicle (100 mile, 150 mile and 250 mile ranges).

Vehicle Efficiency (Fuel)

Light-duty cars



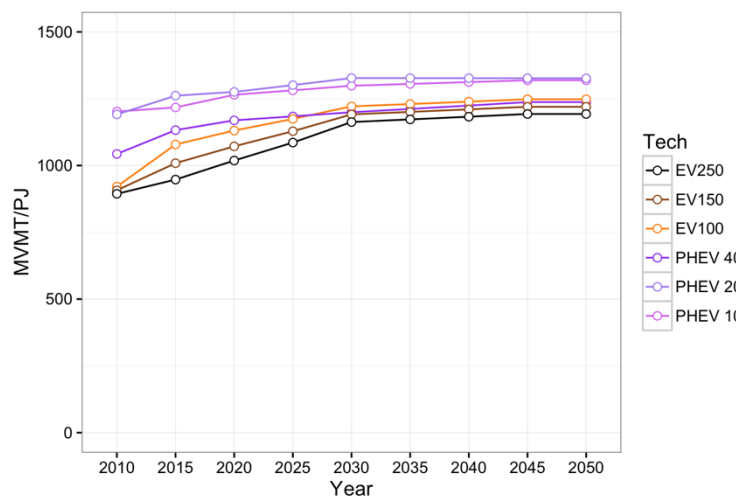
Light-duty trucks



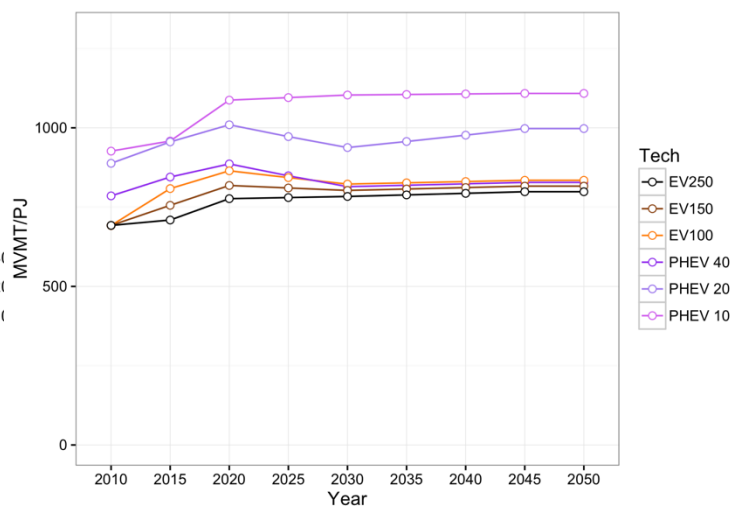
G.Hybrid: Gasoline Hybrid; D: Hybrid: Diesel Hybrid; PHEV: Plugin-Hybrid (10-mile, 20-mile and 40-mile range vehicles); FCV: Fuel cell vehicle; EV: Electric Vehicle (100 mile, 150 mile and 250 mile ranges).

Vehicle Efficiency (Electricity)

Light-duty cars



Light-duty trucks



G.Hybrid: Gasoline Hybrid; D: Hybrid: Diesel Hybrid; PHEV: Plug-in-Hybrid (10-mile, 20-mile and 40-mile range vehicles); FCV: Fuel cell vehicle; EV: Electric Vehicle (100 mile, 150 mile and 250 mile ranges).