GeoCVCM: A spatial consumer vehicle choice model to analyze near-term transitions of advanced technologies
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Project Description
The research project focuses on developing a spatially detailed analysis of consumer choice, with an emphasis on linking consumer utility with geographic specification of the locations of alternative fuel stations and electric vehicle charging availability in specific high-interest geographic areas.

Key Research Questions
- How do the locations and numbers of hydrogen stations and public chargers influence the alternative vehicle purchases at a local level?
- How do sales for alternative fueled vehicles vary spatially?
- What are likely sales and fleet shares of hydrogen fuel cell vehicles and plug-in electric vehicles in study regions out to 2030?

Background and Motivation
- The consumer choice models developed so far operate on a rather spatially aggregated level, either at a state level.
- Even though these models include 'non-monetary costs' to characterize the perceptions of consumers towards vehicle technologies, certain important details are lost while aggregating spatially.
- When these details are aggregated, in nationwide or statewide models, it is assumed that the presence of these stations at a particular location will affect all the consumers, when in fact, the deployment of stations or chargers will only influence potential consumers that are near the deployed infrastructure.
- Hence, characterizing the spatial dimension of consumers and their proximity to fuel infrastructure is very important for improving the representation of vehicle purchase decisions.
- This spatial consumer choice model incorporates the level of utility that is provided by stations and chargers at a fine level of spatial detail, versus assuming some average level of station availability, common to other modeling approaches.
- The model also includes spatially sensitive demographic attributes such as income, driver profile, and so on.

Methodology
- Consumer groups are segmented and characterized based upon demographic and geographic factors such as income, population density, travel distances, housing type, geographic location, risk attitudes, and infrastructure availability.
- A spatial model is developed with a nested multinomial logit (NNML) vehicle choice function at its core, with varying demographic and utility parameters across each population "node".
- Different choice probabilities and market shares for specific vehicle technologies.
- Instead of developing a market share for an entire region, we will instead calculate sales and purchase probability for each micro-region (zip code areas).
- The results are then aggregated for the entire region.

Disutility Costs
- The main disutility cost components used in the model are refueling inconvenience cost (dependent on station availability), range limitation cost (dependent on charger availability), and income preference cost (perception of vehicle prices based on household income).

Model Structure
- Input Module (a)
  - Consumer Group Attributes
  - Social Attitudes
- Compute Module (b)
  - Calculate disutility cost
- Output Module (d)
  - Final analysis
  - Model runs

Vehicle Technologies
- Conventional
- Hybrid
- Electric
- Fuel Cell
- Plug-in Electric

Model Tools
- The model is built using R programming language and the output is visualized using Google Maps API and Leaflet package.

Preliminary Results
- The model is run for various cities in the northern and southern California regions.
- Preliminary results here focus on areas in two cities: San Francisco and Los Angeles.

Income vs. VMT distribution
- San Francisco
- Los Angeles

Market Share of Vehicle Technologies
- 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.

Regional Outcome
- The results are visualized as purchase probability outcomes at zip code level.

Additional Research Plans
- Infrastructure investment decisions: Once the framework to calculate consumer purchase probabilities on a spatial scale is established, the model can be further developed to calculate optimal station siting decisions for alternative fuel stations, based on which locations would have the greatest impact on future alt fuel adoption.
- Integration with Travel Demand Model: The everyday travel distances and destinations of consumers plays a huge role in deciding what kind of vehicle they would be more willing to purchase. The detailed data from the CSTDM (California Statewide Travel Demand Model) will be a valuable addition to this framework, and it will add a whole new dimension and refine the consumer purchase decisions, based on their daily travel distance, as well the appropriate location of fuel/charging stations in the region.

Relevance to STEPS 2015 to 2018 Programs
- Initiating Transitions 2015-2030: Infrastructure investments play a key role in adoption of alternative vehicles. This framework will offer a platform to better understand how the location of stations can influence the alternative vehicle transitions, especially battery electric cars and fuel cell vehicles. It will enable us to develop scenarios for vehicle adoption in key early markets.
- MAVRIC: This is an improved framework from energy system models, which typically operate on a larger spatial scale. Findings from this model can be compared with larger models, and potentially this framework can be used as a supplementary model to CA-TIMES.
- This work will help broaden our understanding of the role of infrastructure deployment, consumer demographics, spatial and geographic factors, all of which will influence consumers and vehicle adoption.

For example, a consumer living in area ‘A’ close to hydrogen refueling stations has a higher probability to purchase a fuel cell vehicle compared to a person living in area ‘B’. This spatial utility will be quantified in the model for analysis.